European Journal of Operational Research 269 (2018) 35–50

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Environmental efficiency and abatement efficiency measurements of China's thermal power industry: A data envelopment analysis based materials balance approach

Ke Wang[a,b,c,e], Yi-Ming Wei[a,b,c,e], Zhimin Huang[a,b,d,*]

[a] Center for Energy and Environmental Policy Research & School of Management and Economics, Beijing Institute of Technology, Beijing, China
[b] Sustainable Development Research Institute for Economy and Society of Beijing, Beijing, China
[c] Collaborative Innovation Center of Electric Vehicles in Beijing, Beijing, China
[d] Robert B. Willumstad School of Business, Adelphi University, Garden City, NY, USA
[e] Beijing Key Lab of Energy Economics and Environmental Management, Beijing, China

ARTICLE INFO

Article history:
Received 26 August 2016
Accepted 24 April 2017
Available online 27 April 2017

Keywords:
OR in environment and climate change
Electricity generation
Emission reduction
Materials balance principle
Pollutant abatement

ABSTRACT

Appropriate measurement of environmental and emission abatement efficiency is crucial for assisting policy making in line with constructing a more sustainable society. The majority of traditional approaches for environmental efficiency measures take pollutant emissions as either undesirable outputs or environmentally determined inputs which suffer a limitation of not satisfying the physical laws that regulate the operation of economic and environmental process. In this study, we propose a DEA based approach which is combined with the materials balance principle (MBP) that accounts for laws of thermodynamics to jointly evaluate environmental and abatement efficiency. This approach is along the line of weak G-disposability based modelling but is an extension to existing models that in our approach the identification of possible adjustments on polluting mass bound in inputs and outputs, and potential adjustments on abatement of pollutants are all included. The overall environmental efficiency measured by this approach is decomposed into the measures of technical efficiency, polluting inputs allocative efficiency, and polluting and non-polluting inputs allocative efficiency with the emphasizing of incorporating pollutant abatement activities. Accordingly, new measures of abatement efficiency are proposed which help to identify the pollutant abatement potential that can be achieved from end-of-pipe abatement technology promotion associated with polluting input quality promotion and input resources reallocation. Furthermore, several global Malmquist productivity indices for identifying the changes on environmental and abatement efficiency are proposed. This approach is applied to China's thermal power industry and some empirical results verifying the necessity of introducing the MBP are obtained.

© 2017 Elsevier B.V. All rights reserved.

1. Introduction

During the latest two decades, academic researchers, industry entrepreneurs and government officials have increasingly recognized that sustainable development is one of core solutions to balance economic and social development with environment protection and climate change mitigation. Since the emissions of greenhouse (e.g., carbon dioxide, CO_2) and other air pollutants (e.g., sulfur dioxide, SO_2 and oxynitride, NO_x) derived from fossil fuel consumption are the major contributions to global warming and regional atmospheric contamination, the appropriate measurement of environmental efficiency and emission abatement efficiency with sound theoretical base and methodical framework is crucial for making the measure of sustainability and the pursuing of sustainable development accountable and then assisting policy and decision making in line with constructing a more sustainable society. This is more obvious for China's thermal power industry since China is currently the world's largest energy consumer and greenhouse gas emitter. In addition, the thermal power industry consumes approximately 45% of the total primary energy supply and contributes more than 40% of carbon emission in China in 2014 (Wang, Lee, Zhang, & Wei, 2016). To construct a resource saving and environmentally friendly society has become one of China's primary strategies for pursuing sustainable development,

* Corresponding author at: Robert B. Willumstad School of Business, Adelphi University, Garden City, NY, USA.
E-mail address: huang@adelphi.edu (Z. Huang).

http://dx.doi.org/10.1016/j.ejor.2017.04.053
0377-2217/© 2017 Elsevier B.V. All rights reserved.

and to promote environmental and abatement efficiency has also become a major policy in China's thermal power industry in which the net coal consumption rate,[1] and the total amounts of SO_2 and NO_x emissions of electricity generation are regulated to reduce by 12%, 41% and 29%, respectively, during China's 11th and 12th Five Year Plan (FYP) periods (2006–2010 and 2011–2015) (SCC, 2007; SERC 2011; Wang, Zhang, Yu, Wei, & Wang, 2016). As the government and the industry has begun to implement mechanism to reduce carbon emission and air pollutants, mathematical modelling of environmental and abatement efficiency that provide more accurate and deep insight information to national environmental policy making and thermal power industry decision making would help to promote the performances of environmental management and sustainable development.

One line of cutting-edge research on this issue has applied the widely accepted Data Envelopment Analysis (DEA) (Banker, Charnes, & Cooper, 1984; Charnes, Cooper, & Rhodes, 1978; Cooper et al., 2011; Zhu, 2014) to develop efficiency and productivity evaluation models for decision making units (DMU), e.g., thermal power industry sector in this study, that contain both normal input and output variables (i.e., energy, labour, capital, and electricity) and variables that measure undesirable outputs, e.g., greenhouse gas and other pollutants. In the presence of including environmental regulations in efficiency evaluation of thermal power industry, both desirable output and undesirable output need to be modelled simultaneously, since the reduction of pollution might result in diverting some desirable output and input to pollution abatement activities (Adler & Volta, 2016; Dakpo, Jeanneaux, & Latruffe, 2016). In the literature applying DEA method, the modelling of undesirable outputs has been formalized in several ways as (i) treating pollutions as free disposable inputs (Hailu & Veeman, 2001); (ii) treating pollutions as weak disposable outputs (Färe & Grosskopf, 2004; Färe, Grosskopf, Lovell, & Pasurka, 1989); (iii) treating pollutions as multiplicative inverse outputs or as large constant added additive inverse outputs (Sahoo, Luptacik, & Mahlberg, 2011; Scheel, 2001; Seiford & Zhu, 2002, 2005); (iv) using two sub-technologies generating desirable output and undesirable output separately (e.g., by-production method and natural/managerial disposability method) (Murty, Russell, & Levkoff, 2012; Sueyoshi and Goto 2012); (v) using the materials balance principle (MBP) to include the laws of thermodynamics (e.g., weak G-disposability method) (Coelli, Lauwers, & Van Huylenbroeck, 2007; Hampf & Rødseth, 2015; Welch & Barnum, 2009).

The method of treating undesirable outputs as inputs has been seriously challenged as it does not reflect the real production process and does not satisfy the physical laws. The idea of undesirable output data transformation (multiplicative inverse or additive inverse) has also been challenged since the results obtained from it are inconsistent. With respect to the assumption of weak disposability of undesirable output, there are also several weaknesses in efficiency measures, for instance, it violates the monotonicity in the production of undesirable output and thus may lead to inappropriate estimation of shadow price of pollution; it may evaluate strongly dominated DMU as efficient, and which may be further used as target for benchmarking (Chen & Delmas, 2012; Leleu, 2013). Furthermore, there is another argument against weak disposability that it is not consistent with the laws of thermodynamics in the case that the end-of-pipe abatement is not available (Dakpo et al., 2016; Førsund, 2009; Hampf & Rødseth, 2015).

The violation of physical laws of the above methods may result in inaccurate estimation of environmental efficiency, especially when physical productivity is of concern, which is highlighted in the modelling of air pollutant emissions from electricity generation (Hampf, 2014; Welch & Barnum, 2009). Therefore, in this study we incorporate the materials balance principle which accounts for the laws of thermodynamics in our modelling and propose several DEA based models for environmental efficiency and abatement efficiency evaluation. The major contribution of this study is that our approach is along the same line of weak G-disposability assumption based modelling but is an extension to existing models, since our approach highlights the identification of all possible adjustments on polluting mass bound in inputs and outputs, as well as potential adjustments on abatement of pollutants. In addition, our approach decomposes the overall environmental efficiency measure into technical efficiency, polluting inputs allocative efficiency, and polluting and non-polluting inputs allocative efficiency measures with the emphasis on the modelling of pollution abatement activities in the efficiency measures. Accordingly, several new measures of abatement efficiency are developed. Furthermore, we propose several global Malmquist productivity indices to additionally identify the changes on environmental and abatement efficiency. Our approach is applied to China's thermal power industry. The regional environmental and abatement efficiency levels and the trends of efficiency movements, as well as the associated emission reduction potentials and abatement improvement potentials on air pollutants for this industry are estimated. There have been several mathematical programming based or parametric model based studies that address the energy and environmental efficiency evaluation of China's electricity industry (e.g., Bi, Song, Zhou, & Liang, 2014; Du, He, & Yan, 2013; Duan, Guo, & Xie, 2016; Yang & Pollitt, 2009; Zhao, Yin, & Zhao, 2015), however, none of them, to our knowledge, has properly address the materials balance principle. Our paper is the first attempt to implement the DEA based MBP approach empirically in China's thermal power industry. Our empirical study verifies that there were overall environmental efficiency promotion in China's thermal power industry and identifies that this promotion was mainly derived from the quality promotion on coal utilized for electricity generation and the structure optimization on polluting and non-polluting input mix in China's thermal power industry.

The remainder of this paper is organized as follows. The next section explains the proposed materials balance approach for environmental and abatement efficiency evaluation. Section 3 presents the application to China's thermal power industry. The summary and conclusion are provided in the final section.

2. Materials balance approach for environmental and abatement efficiency measurements

In this section, we start by introducing the materials balance approach for modelling environmental and abatement technologies. Then, we introduce three generalized nonparametric optimization models for estimating the minimal amounts of pollutions for given desirable outputs and (i) fixed inputs, (ii) fixed non-polluting inputs, and (iii) variable inputs, respectively. These minimal amounts of pollutions are used for measuring environmental efficiency which can be additionally decomposed into technical environmental efficiency and input allocative environmental efficiency. In addition, the pollution abatement activity is included in our modelling and thus, several new measures of abatement efficiency are proposed in this section.

2.1. Environmental production technology with materials balance principle

The studies in environmental economics modelling emphasize the role of the laws of thermodynamics in determining pollution of production processes. However, the majority of the traditional

[1] Net coal consumption rate of electricity generation is defined as the amount of coal consumption per unit of electricity generation, and the measure of this indicator is gram per kilowatt hour.

approaches for environmental performance measures take the environmental effect (e.g., the emission of pollutant) as either an undesirable output or an environmentally determined input in modelling (e.g., Chung, Färe, & Grosskopf, 1997; Färe, Grosskopf, & Pasurka, 2007a, 2007b; Wang, Wei, & Zhang, 2012, 2013; Zhou, Ang, & Poh, 2006). These approaches suffer a serious limitation that they do not satisfy the laws of thermodynamics (i.e., the law of conservation of mass and energy, and the law of non-conservation of entropy) which regulate the operation of economic and environmental process (Coelli et al., 2007; Hampf & Rødseth, 2015; Hoang & Coelli, 2011; Hoang & Rao, 2010; Rødseth, 2016; Welch & Barnum, 2009). In order to account for the laws of thermodynamics, the materials balance principle is introduced in the environmental production technology[2] which states that the total amount of mass (i.e., material or energy) in the inputs must equal the mass in desirable outputs plus the mass in the residuals which (may) cause pollution (Ayres & Kneese, 1969; Coelli et al., 2007). The balance of materials can be defined as:

$$\boldsymbol{\alpha x} - \boldsymbol{\beta y} = \boldsymbol{b} + \boldsymbol{a} \tag{1}$$

where $\boldsymbol{x}$, $\boldsymbol{y}$ and $\boldsymbol{b}$ are the vectors of inputs, desirable outputs and emitted undesirable outputs (pollutants); $\boldsymbol{a}$ is a vector of the amount of abatements of pollutants; $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ represent the vectors of unit mass bound in the inputs (e.g., emission factors) and the vectors of unit mass bound in the desirable outputs (e.g., recuperation factors). In Eq. (1), the component of $\boldsymbol{\alpha}$ associated with the non-polluting input is zero, and the component associated with polluting input is non-zero. Similarly, the component of $\boldsymbol{\beta}$ is zero for the desirable output that does not contain polluting mass, and is non-zero for the desirable output with polluting mass. $\boldsymbol{a} = 0$ if no abatement activity for pollutant emission is presented, and $\boldsymbol{a} > 0$ if abatement activity is implemented.

In traditional joint production environmental technology (Färe et al., 1989), the weak disposability assumption on undesirable is applied[3]. However, this assumption is not always consistent with the materials balance principle but only when the end-of-pipe pollutant abatement activities are possible and the amount of abatement can be adjusted. Furthermore, the null jointness and inactivity assumption associated with the traditional joint production environmental technology may violate the thermodynamics law of non-conservation of entropy. Recently, Hampf and Rødseth (2015) and Rødseth (2016) proposed environmental economics model that satisfies the materials balance principle and obeys the laws of thermodynamics. Their model is based on the original concept of G-disposability proposed by Chung (1997) and is extended to a summing-up formulation which is defined as weak G-disposability. This assumption implies that the increase in pollutant ($\Delta\boldsymbol{b}$) must equals the sum of (i) the increase in polluting mass bound in input ($\boldsymbol{\alpha}\Delta\boldsymbol{x}$), (ii) the reduction in polluting mass bound in desirable output ($\boldsymbol{\beta}\Delta\boldsymbol{y}$), and (iii) the reduction in abatement of pollutant ($\Delta\boldsymbol{a}$). The summing-up formulation of weak G-disposability can be defined as:

$$\Delta\boldsymbol{b} = \boldsymbol{\alpha}\Delta\boldsymbol{x} + \boldsymbol{\beta}\Delta\boldsymbol{y} + \Delta\boldsymbol{a} \tag{2}$$

Since the increase in pollutant is due to the increase in the consumption of polluting input and/or the reduction in the production of desirable output, as well as the decrease in the amount of pollutant abatement, Eq. (2) is in line with Eq. (1).

Proof. Suppose $\boldsymbol{b}'=\boldsymbol{b}+\Delta\boldsymbol{b}$, $\boldsymbol{x}'=\boldsymbol{x}+\Delta\boldsymbol{x}$, $\boldsymbol{y}'=\boldsymbol{y}-\Delta\boldsymbol{y}$, and $\boldsymbol{a}'=\boldsymbol{a}-\Delta\boldsymbol{a}$. According to Eq. (1), we have $\boldsymbol{b}'=\boldsymbol{\alpha x}'-\boldsymbol{\beta y}'-\boldsymbol{a}'$, which can be written as $\boldsymbol{b}+\Delta\boldsymbol{b}=\boldsymbol{\alpha}(\boldsymbol{x}+\Delta\boldsymbol{x})-\boldsymbol{\beta}(\boldsymbol{y}-\Delta\boldsymbol{y})-(\boldsymbol{a}-\Delta\boldsymbol{a})=\boldsymbol{\alpha x}-\boldsymbol{\beta y}-\boldsymbol{a}+\boldsymbol{\alpha}\Delta\boldsymbol{x}+\boldsymbol{\beta}\Delta\boldsymbol{y}+\Delta\boldsymbol{a}$. Since $\boldsymbol{b}=\boldsymbol{\alpha x}-\boldsymbol{\beta y}-\boldsymbol{a}$, then we have $\Delta\boldsymbol{b}=\boldsymbol{\alpha}\Delta\boldsymbol{x}+\boldsymbol{\beta}\Delta\boldsymbol{y}+\Delta\boldsymbol{a}$.

Before moving to introduce the efficiency estimation model, we would like to clarify that the concept of MBP does not necessarily mean that the amount of a certain type of material in the input must be identical to that in the desirable or undesirable output; unless nuclear reaction process occurs, material balances are maintained at the level of chemical elements. Thus, the MBP applied in this study only valid when specific type of process with corresponding chemical reaction is assumed (i.e., thermal electricity generation process in this study), but not for physical segregation (e.g., nuclear electricity generation process). In addition, we would like to point out that in some applications of industrial efficiency estimation, several existing methods are consistent with the MBP. For instance, in the coal-fired electricity generation case, there is no mass of carbon or sulphur in the electricity output, and thus the efficiency estimation that only expand desirable outputs with ratio θ (x, θy, b), or just contract inputs and undesirable outputs simultaneously with ratio θ (x/θ, y, b/θ) will still conform the MBP; however, the hyperbolic efficiency estimation (x/θ, θy, b/θ) will violate the MBP.

2.2. DEA based estimation of environmental and abatement efficiency

In this study, we use DEA method to estimate environmental efficiency with the pollution abatement efforts taken into account. DEA, as a non-parametric approach, does not need assumptions on the DMUs' behaviour, the specific functional form of production function, or the efficiency distribution. Suppose there is a sample of n DMUs with the inputs, desirable outputs and undesirable outputs denoted by (x_{ij}, y_{rj}, b_{fj}), where $i=1, \ldots, m$, $r=1, \ldots, s$, $f=1, \ldots, h$, and $j=1, \ldots, n$. Furthermore, we assume the first m_1 inputs x_{ij}, $i=1, \ldots, m_1$ are polluting inputs (x^P), while the remaining m–m_1 inputs x_{ij}, $i=m_1+1, \ldots, m$ are non-polluting inputs (x^{NP}). Similarly, we assume the first s_1 desirable outputs y_{rj}, $r=1, \ldots, s_1$ do not contain polluting mass (y^{NP}), while the remaining s–s_1 desirable outputs y_{rj}, $r=s_1+1, \ldots, s$ contain polluting mass (y^P). b_{fj}, $f=1, \ldots, h$ are utilized to represent the discharged undesirable outputs, i.e., emitted pollutions. To include the pollution abatement activity, we use a_{fj}, $f=1,..,h_1$, to denote the amount of abatement of pollutants. Note that we assume the first h_1 pollutions b_{fj}, $f=1, \ldots, h_1$ are controllable, while the other pollutions are uncontrolled emissions, i.e., there are no abatement activities on these pollutions. Therefore, $b_{fj}+a_{fj}$, $f=1,..,h_1$, are the total amount of controllable pollutions produced, while b_{fj}, $f=h_1+1,\ldots h$, denote both the produced and emitted uncontrolled pollutions. Then, the corresponding estimation of environmental and abatement efficiency with the materials balance principle can be obtained based on the following minimization programming (1):

$$B_{FI} = \min_{\lambda,b,d} \frac{1}{h}\sum_{f=1}^{h} b_f^{FI} \tag{1}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj}^P - d_r^{y^P} = y_{rj_0}^P, \quad r = 1, \ldots, s_1 \tag{1.1}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj}^{NP} - d_r^{y^{NP}} = y_{rj_0}^{NP}, \quad r = s_1+1, \ldots, s \tag{1.2}$$

$$\sum_{j=1}^{n} \lambda_j b_{fj} + d_f^b = b_f^{FI}, \quad f = 1, \ldots h \tag{1.3}$$

---

[2] The environmental production technology set is a collection of all technically possible input, desirable and undesirable output combinations which is defined as: $\boldsymbol{T}$={($\boldsymbol{x}$, $\boldsymbol{y}$, $\boldsymbol{b}^+$): $\boldsymbol{x}$ can produce ($\boldsymbol{y}$, $\boldsymbol{b}^+$)}, where $\boldsymbol{b}^+=\boldsymbol{b}+\boldsymbol{a}$.

[3] The weak disposability of undesirable outputs associated with desirable outputs is defined as: If ($\boldsymbol{x}$, $\boldsymbol{y}$, $\boldsymbol{b}$)∈$\boldsymbol{T}$ and $0\le\rho\le1$, then ($\boldsymbol{x}$, $\rho\boldsymbol{y}$, $\rho\boldsymbol{b}$)∈$\boldsymbol{T}$. This assumption implies that to reduce undesirable outputs needs to increase some inputs and/or leads to reduce some desirable outputs with the same proportion, i.e., there must be some cost in contrasting undesirable outputs.

$$\sum_{j=1}^{n}\lambda_j x_{ij}^P + d_i^{x^P} = x_{ij_0}^P, \quad i=1,\ldots,m_1 \tag{1.4}$$

$$\sum_{j=1}^{n}\lambda_j x_{ij}^{NP} + d_i^{x^{NP}} = x_{ij_0}^{NP}, \quad i=m_1+1,\ldots,m \tag{1.5}$$

$$\sum_{j=1}^{n}\lambda_j a_{fj} - d_f^{a^{FI}} = a_{fj_0}, \quad f=1,\ldots,h_1 \tag{1.6}$$

$$\sum_{i=1}^{m_1}\alpha_{fi} d_i^{x^P} + \sum_{r=1}^{s_1}\beta_{fr} d_r^{y^P} = b_{fj_0} - b_f^{FI} - d_f^{a^{FI}}, \quad f=1,\ldots,h_1 \tag{1.7}$$

$$\sum_{i=1}^{m_1}\alpha_{fi} d_i^{x^P} + \sum_{r=1}^{s_1}\beta_{fr} d_r^{y^P} = b_{fj_0} - b_f^{FI}, \quad f=h_1+1,\ldots,h \tag{1.8}$$

The objective of Model (1) is to achieve the minimal amount of all h pollution b_f^{FI}, $f=1, \ldots, h$ with the given desirable outputs (both y^{NP} and y^P) unchanged and all the inputs (both x^{NP} and x^P) fixed for the currently under estimating DMU$_{j0}$. We use *FI* to denote such "fixed input" scenario. In Model (1), λ_j denotes the intensity variable representing convex combination among the DMUs; $d_r^{y^{NP}}$, $d_r^{y^P}$, $d_i^{x^{NP}}$, $d_i^{x^P}$, d_f^b and $d_f^{a^{FI}}$ are the slack variables helped to implement the weak G-disposability assumption in the modeling of materials balance principle; α_{fi} and β_{fr} are factors indicating the unit mass bound in polluting inputs and the unit mass bound in desirable outputs containing polluting mass. Note that λ, b, d are decision variables, and all other characters represent parameters in Model (1). Constraints (1.1)–(1.5) are associated with polluting desirable outputs, non-polluting desirable outputs, emitted pollutions, polluting inputs, and non-polluting inputs, respectively. Constraint (1.6) is related to abatement of pollutions. Constraints (1.7) and (1.8) guarantee the materials balance principle that the increase in pollutant ($\Delta b_f = b_{fj_0} - b_f^{FI}$) must equals the (i) sum of the increase in polluting mass bound in input ($\alpha\Delta x = \sum_{i=1}^{m_1}\alpha_{fi} d_i^{x^P}$), (ii) the reduction in polluting mass bound in desirable output ($\beta\Delta y = \sum_{r=1}^{s_1}\beta_{fr} d_r^{y^P}$), and (iii) the reduction in abatement of pollutant ($\Delta a = d_f^{a^{FI}}$). The third component is not necessary for the uncontrolled pollutions as shown in Constraint (1.8).

Model (2) extends Model (1) through additionally allowing the polluting input (x^P) changeable but the non-polluting inputs (x^{NP}) fixed, and we use *FNPI* to denote this "fixed non-polluting input" scenario. Therefore, the objective of Model (2) is to achieve the minimal amount of all h pollution b_f^{FNPI}, $f=1, \ldots, h$ with the given desirable outputs unchanged and all the non-polluting inputs fixed:

$$B_{FNPI} = \min_{\lambda,b,d,x^P} \frac{1}{h}\sum_{f=1}^{h} b_f^{FNPI} \tag{2}$$

$$\sum_{j=1}^{n}\lambda_j y_{rj}^P - d_r^{y^P} = y_{rj_0}^P, \quad r=1,\ldots,s_1 \tag{2.1}$$

$$\sum_{j=1}^{n}\lambda_j y_{rj}^{NP} - d_r^{y^{NP}} = y_{rj_0}^{NP}, \quad r=s_1+1,\ldots,s \tag{2.2}$$

$$\sum_{j=1}^{n}\lambda_j b_{fj} + d_f^b = b_f^{FNPI}, \quad f=1,\ldots h \tag{2.3}$$

$$\sum_{j=1}^{n}\lambda_j x_{ij}^P + d_i^{x^P} = x_i^P, \quad i=1,\ldots,m_1 \tag{2.4}$$

$$\sum_{j=1}^{n}\lambda_j x_{ij}^{NP} + d_i^{x^{NP}} = x_{ij_0}^{NP}, \quad i=m_1+1,\ldots,m \tag{2.5}$$

$$\sum_{j=1}^{n}\lambda_j a_{fj} - d_f^{a^{FNPI}} = a_{fj_0}, \quad f=1,\ldots,h_1 \tag{2.6}$$

$$\sum_{i=1}^{m_1}\alpha_{fi}\left(x_{ij_0}^P - x_i^P\right) + \sum_{r=1}^{s_1}\beta_{fr} d_r^{y^P} = b_{fj_0} - b_f^{FNPI} - d_f^{a^{FNPI}}, \quad f=1,\ldots,h_1 \tag{2.7}$$

$$\sum_{i=1}^{m_1}\alpha_{fi}\left(x_{ij_0}^P - x_i^P\right) + \sum_{r=1}^{s_1}\beta_{fr} d_r^{y^P} = b_{fj_0} - b_f^{FNPI}, \quad f=h_1+1,\ldots,h \tag{2.8}$$

In Model (2), λ, b, d and x^P are decision variables. Constraint (2.4) is different from Constraint (1.4) for allowing polluting input adjustable, which indicates that DMU is capable to adjust its polluting input mix so as to additionally reduce its production of pollutions. Constraints (2.7) and (2.8) guarantee the materials balance principle. Note that since the polluting inputs are changeable, the sum of the increase in polluting mass bound in input $\alpha\Delta x$ is represented by $\sum_{i=1}^{m_1}\alpha_{fi}(x_{ij_0}^P - x_i^P)$ instead of $\sum_{i=1}^{m_1}\alpha_{fi} d_i^{x^P}$.

At last, we propose Model (3) which allowing all the input variable and we use *VI* to denote such "variable input" scenario. The objective of Model (3) is to achieve the minimal amount of all h pollution b_f^{VI}, $f=1, \ldots, h$ with the given desirable outputs unchanged and all the inputs adjustable:

$$B_{VI} = \min_{\lambda,b,d,x} \frac{1}{h}\sum_{f=1}^{h} b_f^{VI} \tag{3}$$

$$\sum_{j=1}^{n}\lambda_j y_{rj}^P - d_r^{y^P} = y_{rj_0}^P, \quad r=1,\ldots,s_1 \tag{3.1}$$

$$\sum_{j=1}^{n}\lambda_j y_{rj}^{NP} - d_r^{y^{NP}} = y_{rj_0}^{NP}, \quad r=s_1+1,\ldots,s \tag{3.2}$$

$$\sum_{j=1}^{n}\lambda_j b_{fj} + d_f^b = b_f^{VI}, \quad f=1,\ldots h \tag{3.3}$$

$$\sum_{j=1}^{n}\lambda_j x_{ij}^P + d_i^{x^P} = x_i^P, \quad i=1,\ldots,m_1 \tag{3.4}$$

$$\sum_{j=1}^{n}\lambda_j x_{ij}^{NP} + d_i^{x^{NP}} = x_i^{NP}, \quad i=m_1+1,\ldots,m \tag{3.5}$$

$$\sum_{j=1}^{n}\lambda_j a_{fj} - d_f^{a^{VI}} = a_{fj_0}, \quad f=1,\ldots,h_1 \tag{3.6}$$

$$\sum_{i=1}^{m_1}\alpha_{fi}\left(x_{ij_0}^P - x_i^P\right) + \sum_{r=1}^{s_1}\beta_{fr} d_r^{y^P} = b_{fj_0} - b_f^{VI} - d_f^{a^{VI}}, \quad f=1,\ldots,h_1 \tag{3.7}$$

$$\sum_{i=1}^{m_1}\alpha_{fi}\left(x_{ij_0}^P - x_i^P\right) + \sum_{r=1}^{s_1}\beta_{fr} d_r^{y^P} = b_{fj_0} - b_f^{VI}, \quad f=h_1+1,\ldots,h \tag{3.8}$$

In Model (3), λ, b, d, x^{NP} and x^P are decision variables. Constraints (3.4) and (3.5) indicate that both the polluting and non-polluting inputs are variable which provides the DMU the ability to adjust its input mix for further reducing its production of pollutions.

Models (1), (2), (3), respectively, provides the minimal total amount of pollutions given the desirable outputs unchanged and (i) the inputs fixed, (ii) the non-polluting inputs fixed but polluting inputs adjustable, and (iii) all the inputs adjustable. These three

scenarios refer to three different strategies to minimizing pollutions with three different degrees of freedom to adjust the polluting and non-polluting input mix. Then, the associated environmental and abatement efficiency could be measured as follows:

$$\text{Overall environmental efficiency } (OE) = \frac{B_{VI}}{B} \tag{4}$$

$$\text{Technical environmental efficiency } (TE) = \frac{B_{FI}}{B} \tag{5}$$

$$\text{Polluting input allocative environmental efficiency } (PAE) = \frac{B_{FNPI}}{B_{FI}} \tag{6}$$

$$\text{Non}-\text{polluting and polluting input allocative environmental efficiency } (NAE) = \frac{B_{VI}}{B_{FNPI}} \tag{7}$$

Based on the above definition, we have the following decomposition:

$$OE = \frac{B_{VI}}{B} = TE \times PAE \times NAE = \frac{B_{FI}}{B} \times \frac{B_{FNPI}}{B_{FI}} \times \frac{B_{VI}}{B_{FNPI}} \tag{8}$$

In Eqs. (4), (5) and (8), $B = \frac{1}{h}\sum_{f=1}^{h} b_f$, which is the observed average level of all pollutions of the DMU under evaluation. The technical environmental efficiency and the allocative environmental efficiency implies the largest reduction potential achievable on average pollution through technology promotion and input resources (both polluting and non-polluting input resources) reallocation, respectively; while the overall environmental efficiency revels the largest reduction potential achievable on average pollution through the combined action of technology promotion and resources reallocation.

In addition, we could similarly define and decompose the environmental and abatement efficiency for a specific pollution $b_f, f=1, \ldots, h$ as:

$$OE_f = \frac{b_f^{VI}}{b_f} = TE_f \times PAE_f \times NAE_f = \frac{b_f^{FI}}{b_f} \times \frac{b_f^{FNPI}}{b_f^{FI}} \times \frac{b_f^{VI}}{b_f^{FNPI}}, \quad f = 1, \ldots, h \tag{9}$$

in which Specific overall environmental efficiency (OE_f) = Specific technical environmental efficiency (TE_f) × Specific polluting input allocative environmental efficiency (PAE_f) × Specific non-polluting & polluting input allocative environmental efficiency (NAE_f).

Since $d_f^{a^{FI}}$, $d_f^{a^{FNPI}}$, $d_f^{a^{VI}}$ represent the slacks associated with pollution abatements in three different strategies to minimizing pollutions, and a_f represents the observed amount of pollution abated, we could correspondingly define three pollution abatement efficiency measures for each controllable pollution as:

$$\text{Technical abatement efficiency } (ATE_f) = 1 - \frac{d_f^{a^{FI}}}{a_f + d_f^{a^{FI}}}, \quad f = 1, \ldots, h_1 \tag{10}$$

$$\text{Polluting input allocative abatement efficiency } (APAE_f) = 1 - \frac{d_f^{a^{FNPI}}}{a_f + d_f^{a^{FNPI}}}, \quad f = 1, \ldots, h_1 \tag{11}$$

$$\text{Non}-\text{polluting and polluting input allocative abatement efficiency } (ANAE_f) = 1 - \frac{d_f^{a^{VI}}}{a_f + d_f^{a^{VI}}}, \quad f = 1, \ldots, h_1 \tag{12}$$

ATE_f, $APAE_f$ and $ANAE_f$, $f=1, \ldots, h_1$, represent the specific pollution abatement efficiency of a DMU when its (i) all inputs are fixed, (ii) non-polluting inputs are fixed, and (iii) all inputs are variable, respectively. As a matter of fact, these three abatement efficiency measures identify the pollutant abatement potentials achievable from abatement technology promotion (i) without input resources reallocation, (ii) associated with polluting input resources reallocation, i.e., energy input mix adjustment, and (iii) associated with all input resources reallocation, i.e., all input mix adjustment.

The values of both OE and OE_f, as well as their components TE, PAE, NAE, TE_f, PAE_f, NAE_f obtained from Eqs. (4)–(9) are between 0 and 1, where 1 indicates the associated DMU under evaluation is efficient, while value less than 1 indicates inefficient. OE and OE_f measure the capacity of each DMU for minimizing its emitted pollutions given its production of desirable outputs. In addition, the components of OE and OE_f measure the contributions of three different pollution abatement strategies for minimizing emitted pollutions. These strategies are (i) increasing technical efficiency for given inputs (TE and TE_f); (ii) further increasing input allocative efficiency by minimizing the polluting material inflow, i.e., reallocating polluting inputs (PAE and PAE_f); and (iii) additional increasing input allocative efficiency by reallocating both polluting and non-polluting inputs (NAE and NAE_f). We emphases that, since the pollution abatement activity is taken into account in our modelling, the minimization of emitted pollutions can be obtained from both reducing the production of pollutions (controllable and uncontrolled) and increasing the amount of abatement of pollutions (controllable) which are captured through the sixth and seventh constrains in Models (1), (2), (3), respectively. Therefore, three measures of pollution abatement efficiency associated with the above three pollution abatement strategies can be additionally obtained through Eqs. (10)–(12) which also take values between 0 and 1, where 1 indicates the associated DMU under evaluation is efficient in pollution abatement activity, while value less than 1 indicates inefficient.

2.3. Measurements of environmental and abatement efficiency change

The Malmquist productivity index is a commonly used technique for estimating the productive efficiency changes. Traditional Malmquist productivity index (Caves, Christensen, & Diewert, 1982; Färe, Grosskopf, Lindgren, & Roos, 1992) has several disadvantages in utilization such as the existence of infeasible solution, not circular index, or inconsistent measures of cross-period observations (Färe & Grosskopf, 1996; Wang & Wei, 2016). The global Malmquist index proposed by Pastor and Lovell (2005) is one solution to these weaknesses. This productivity index is immune to infeasible solution, satisfies circularity, and generates a single measure for cross-period observations, which has been employed by many studies in empirical analysis (e.g., Fan, Shao, & Yang, 2015; Oh 2010; Wang, Xian, Wei, & Huang, 2016). In this paper, we provide a measurement of the environmental and abatement efficiency change based on the global Malmquist productivity index.

Consider we have a panel data set of t time periods, $t=1,2, \ldots, P$, a global environmental production technology set is defined as $T^G = T^1 \cup T^2 \cup \ldots \cup T^P$, where T^t, $t=1,2, \ldots, P$, is the environmental production technology set for each period. Then, the global environmental Malmquist index for detecting the overall environmental efficiency change from period s to t, $s=1,2, \ldots, P$, $t=1,2, \ldots, P$, $t>s$, for the DMU under evaluation (OEC^{st}) can be calculated as:

$$OEC^{st} = \frac{OE^{Gt}}{OE^{Gs}} = \frac{B_{VI}^{Gt}/B^t}{B_{VI}^{Gs}/B^s} \tag{13}$$

In Eq. (13), $B_{VI}^{Gt} = B_{VI}^{G}(x^t, y^t, b^t, a^t)$ and $B_{VI}^{Gs} = B_{VI}^{G}(x^s, y^s, b^s, a^s)$, which are obtained by solving Model (3) through utilizing the input and output data of period t and s for the DMU under evaluation but taking the global environmental production technology set T^G as reference set, while B^t and B^s are the observed average

level of all pollutions of the DMU under evaluation in period t and s, respectively.

The overall environmental efficiency change from period s to t (OEC^{st}) can be additionally decomposed into technical environmental efficiency change (TEC^{st}), polluting input allocative environmental efficiency change ($PAEC^{st}$), and non-polluting & polluting input allocative environmental efficiency change ($NAEC^{st}$) during the same period as follows:

$$OEC^{st} = \frac{OE^{Gt}}{OE^{Gs}} = \frac{TE^{Gt} \times PAE^{Gt} \times NAE^{Gt}}{TE^{Gs} \times PAE^{Gs} \times NAE^{Gs}} = TEC^{st} \times PAEC^{st} \times NAEC^{st} \tag{14}$$

in which

$$TE^{Gt} = \frac{B_{FI}^{Gt}}{B^t} \text{ and } TE^{Gs} = \frac{B_{FI}^{Gs}}{B^s} \tag{15}$$

$$PAE^{Gt} = \frac{B_{FNPI}^{Gt}}{B_{FI}^{Gt}} \text{ and } PAE^{Gs} = \frac{B_{FNPI}^{Gs}}{B_{FI}^{Gs}} \tag{16}$$

$$NAE^{Gt} = \frac{B_{VI}^{Gt}}{B_{FNPI}^{Gt}} \text{ and } NAE^{Gs} = \frac{B_{VI}^{Gs}}{B_{FNPI}^{Gs}} \tag{17}$$

Similarly, in Eqs. (14)–(17), $B_{FI}^{Gt}=B_{FI}^{G}(x^t, y^t, b^t, a^t)$, $B_{FI}^{Gs}=B_{FI}^{G}(x^s, y^s, b^s, a^s)$, $B_{FNPI}^{Gt} = B_{FNPI}^{G}(x^t, y^t, b^t, a^t)$ and $B_{FNPI}^{Gs} = B_{FNPI}^{G}(x^s, y^s, b^s, a^s)$, which are obtained by solving Models (1) and (2) through utilizing the input and output data of period t and s for the DMU under evaluation but taking the global environmental production technology set T^G as reference set, respectively, and the definitions of B_{VI}^{Gt}, B_{VI}^{Gs}, B^t and B^s are same with those in Eq. (13).

Similar indices can be defined for calculating the environmental efficiency change and its components for a specific pollution b_f, $f=1, \ldots, h$ through using the optimized values of b_f^{VI}, b_f^{FI}, b_f^{FNPI}, and the observed vale of b_f, for period s and t following Eqs. (14)–(17) which are omitted here.

Next, we provide the index for calculating the pollution abatement efficiency change for a specific pollution b_f, $f=1, \ldots, h$ from period s to t when (i) all inputs are fixed, $AEC_f^{FI}(s,t)$, (ii) non-polluting inputs are fixed, $AE_f^{FNPI}(s,t)$, and (iii) all inputs are variable, $AE_f^{VI}(s,t)$, associated with three different strategies for pollution abatements as follows:

$$AEC_f^{FI}(s,t) = \frac{AE_f^{FI}(G,t)}{AE_f^{FI}(G,s)} = \frac{AE_f^{FI \cdot G}\left(x^t, y^t, b^t, a^t\right)}{AE_f^{FI \cdot G}(x^s, y^s, b^s, a^s)} \tag{18}$$

$$AE_f^{FNPI}(s,t) = \frac{AE_f^{FNPI}(G,t)}{AE_f^{FNPI}(G,s)} = \frac{AE_f^{FNPI \cdot G}\left(x^t, y^t, b^t, a^t\right)}{AE_f^{FNPI \cdot G}(x^s, y^s, b^s, a^s)} \tag{19}$$

$$AE_f^{VI}(s,t) = \frac{AE_f^{VI}(G,t)}{AE_f^{VI}(G,s)} = \frac{AE_f^{VI \cdot G}\left(x^t, y^t, b^t, a^t\right)}{AE_f^{VI \cdot G}(x^s, y^s, b^s, a^s)} \tag{20}$$

in which $AE_f^{(*) \cdot G}(x^t, y^t, b^t, a^t)$ and $AE_f^{(*) \cdot G}(x^s, y^s, b^s, a^s)$ are obtained by solving Models (1)–(3) with the input and output data of period t and s for DMU under evaluation and the global environmental production technology set T^G as reference set.

The values of the above seven indices are larger than, equal to, or less than 1, indicating the corresponding efficiency improvement, no change, or deterioration, respectively.

To sum up Section 2, we point out that there are several differences between the environmental and abatement efficiency measurements proposed in this paper and the measurements of Rødseth (2016), in which the most important difference is that the latter estimates the minimized emission of pollution for a DMU through directly utilizing the slacks on inputs and outputs with the weak G-disposability assumption so as to introduce the materials balance principle into modelling, while our measurement detects all changes on the polluting mass bound in input and desirable output, as well as the changes on the amount of abatement of pollutant, which include both the effects of a DMU's input and output slacks and the effects of a DMU's potentials on pollution abatement. This measurement guarantees the materials balance principle in environmental and abatement efficiency estimation modelling by identifying all the possible changes on polluting mass bound in inputs and outputs, as well as the potential changes on abatement of pollutants. Both our measurement and Rødseth (2016)'s measurement decompose the contributions of technical efficiency increase, polluting inputs allocative efficiency promotion, and both polluting and non-polluting inputs allocative efficiency promotion to minimize a DMU's pollution emissions, while our measurement additionally emphasize the modelling of pollution abatement activities in the efficiency measure which are omitted in Rødseth (2016) and Hampf and Rødseth (2015) since they assume zero abatement and zero change on abatement of pollutant. Furthermore, we propose several global Malmquist productivity indices in this paper which help to additionally identify the changes on environmental and abatement efficiency.

Before ending this section, we would like to point out that recent studies have provided a two-stage network DEA based framework for separately measuring the production technology and abatement technology of energy system (e.g., Färe, Grosskopf, & Pasurka, 2013; Hampf, 2014). In these studies, the pollutions from the production process are treated as non-disposable intermediate inputs/outputs, and thus the weak disposability assumption is avoided in the modeling, which makes the network environmental DEA model in line with the materials balance principle based DEA model in environmental and abatement efficiency measures. In this study, we do not apply this model because the distribution of input resources for the production process and the abatement process of the thermal power industry is not available, and an arbitrary decomposition of the input resources to these two sub-stages may lead to unreliable evaluation result. Nevertheless, the two-stage network environmental DEA is a good framework in this case, sine the tradeoff of input resources between the production and abatement activities can be identified and then the input resources adjustment strategy for productivity promotion can be derived.

3. Application to China's thermal power industry

In this section, we present the application of the environmental and abatement efficiency measurements to China's regional thermal power industries. We use the observations of China's thermal power industry at provincial level during the period of 2006–2014 which covers China's 11th FYP period and the major years of the 12th FYP period. During these periods, the regulations for major air pollutions control such as SO_2, NO_X, and dust & soot emissions reduction were implemented, while there is no direct regulation for CO_2 emission reduction in China's thermal power industry. The 11th and 12th FYP for Energy Conservation and Emissions Reduction, which are the pollution control legislations of China's central government, regulated that all new constructing and currently operating coal firing units in electricity sector need to install sulfur and nitrogen scrubbing facilities, and those currently operating coal firing units that do not meet the pollution discharge standards need to be upgraded or eliminated (SCC, 2007, 2011).

3.1. Dataset

Existing studies on energy or environmental efficiency evaluation of thermal power industry usually include energy, capital, labor as production inputs, electricity as desirable output, and air pollutants as undesirable outputs. In this study, to make results

Table 1
Summary statistics for input and output data.

Variables		Measures	Units	Mean	St. Dev.	Min	Max
Inputs	x^P	Energy consumption	Tons of ce	40.37	31.64	1.89	148.15
	x_1^{NP}	Installed capacity	Million kW	23.55	18.11	1.22	77.27
	x_2^{NP}	Employee	Thousand persons	91.16	51.73	11.70	220.07
Desirable output	y^{NP}	Electricity generation	Billion kWh	113.78	91.41	7.20	409.89
Undesirable outputs	b_1	CO_2 emission	Million tons	118.02	93.06	5.19	423.38
	b_2	SO_2 emission	Thousand tons	283.56	212.17	7.92	933.07
	b_3	NO_x emission	Thousand tons	265.13	201.08	6.94	874.37
	b_4	Soot emission	Thousand tons	69.15	65.71	0.93	380.03
Abatements	a_1	SO_2 absorbed	Thousand tons	580.59	583.74	1.26	3317.27
	a_2	NO_x absorbed	Thousand tons	42.14	66.50	0.10	381.91
	a_3	Soot absorbed	Million tons	10.07	8.34	0.30	38.33

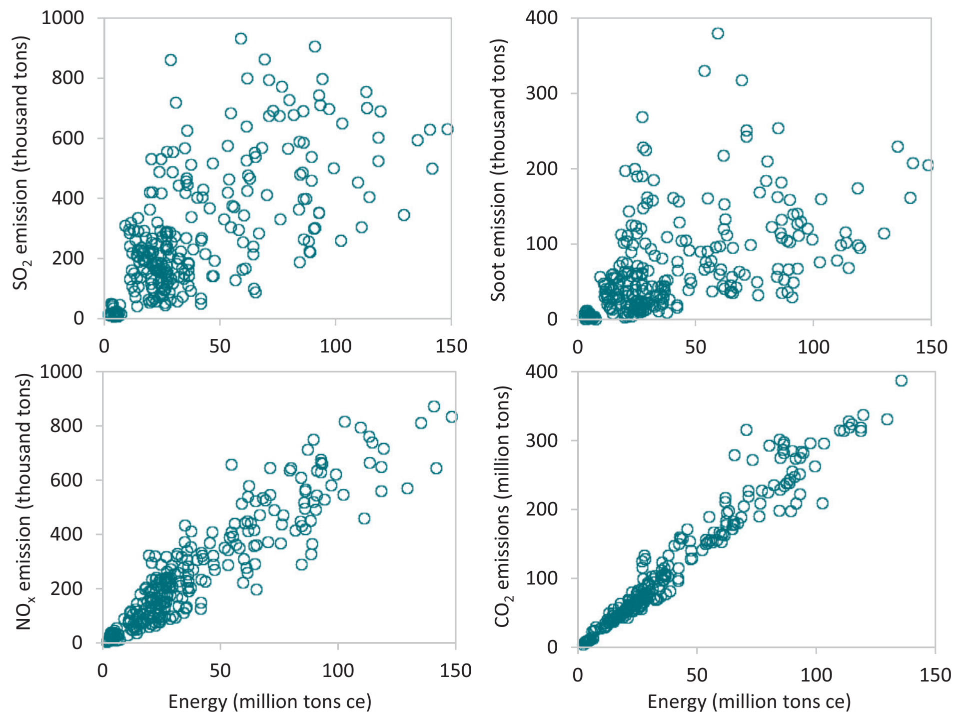

Fig. 1. Energy consumption and emissions.

comparable across all three different strategies to minimizing pollutions, as well as to take abatement activities into efficiency estimation, we include three inputs: (i) polluting input x^P - energy consumption, (ii) non-polluting input x_1^{NP}- installed capacity, and (iii) non-polluting input x_2^{NP}- employee; one desirable output that does not contain polluting mass y^{NP}- electricity generation; and four undesirable outputs come from the combustion of energy: (i) b_1 - CO_2 emission, (ii) b_2 - SO_2 emission, (iii) b_3 - NO_x emission, and (iv) b_4 – Soot emission. In addition, we also include three undesirable output abatements which are realized through end-of-pipe abatement techniques (e.g., scrubber with chemical processes to reduce pollutants): (i) a_1 – absorbed SO_2, (ii) a_2 – absorbed NO_x, and (iii) a_3 – absorbed Soot, to model the abatement activities[4]. Note that the sum of amounts of the emitted and absorbed pollutants (i.e., SO_2, NO_x, and Soot, respectively) equal to the amount that generated (i.e., $b^+=b+a$) as byproduct of electricity generation. We assume there is zero abatement on CO_2, since there is no end-of-pipe abatement activity taking place for CO_2 in China's thermal power industry, excepting for several small pilot carbon capture and storage projects in a few thermal power plants. We calculate the CO_2 emission factors by dividing the emitted (i.e., generated) CO_2 emission on the energy consumed for each provincial thermal power industry sector, while we calculate the SO_2, NO_x and Soot emission factors by dividing the generated (i.e., the sum of the emitted and absorbed) SO_2, NO_x and Soot emissions on the energy consumed for each provincial thermal power industry sector, respectively. These calculations are in line with the MBP.

Table 1 presents the measures and summary statistics of the above input and output data. The collection of these data is explained as follows. Energy consumption data are collected from the energy balance table in China's energy statistical yearbooks (2007–2015) which is the sum of the transformation of coal, oil and natural gas for electricity and is converted into standard coal equivalent (ce) according to the factors provided in China's

[4] End-of-pipe abatement techniques are those technologies such as scrubbers on smokestacks and catalytic convertors on tailpipesw that reduce pollutant emissions after they have formed. These techniques are different for three pollutant emissions in this study. The commonly utilized end-of-pipe abatement techniques in the power industry for SO_2 include wet flue gas desulfurization, spray dry absorbing, and circulating dry scrubbers; while the technique for NO_x abatement is selective catalytic reduction that uses a chemical reaction involving ammonia to convert NO_x to nitrogen and water. In addition, the combination of ceramic filters, which use particle traps, and oxidation catalysts are the most plausible end-of-pipe abatement techniques to reduce Soot particles (Expert Group on Techno-Economic Issues, 2012; European Environment Agency, 2013).

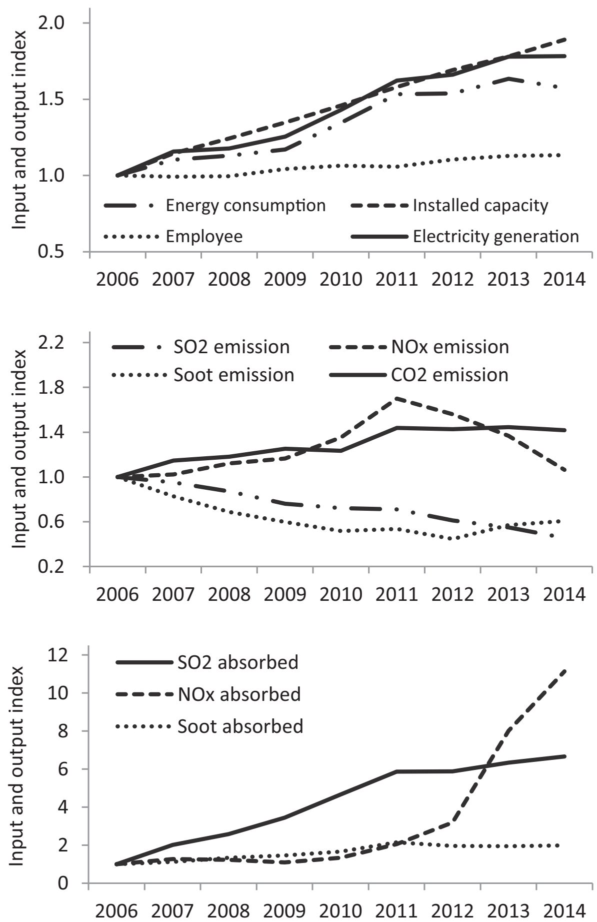

Fig. 2. Input, output and abatement indices.

energy statistical yearbook (2007). Installed capacity data and electricity generation are collected from China's electricity statistical yearbooks (2007-2015). Employee data are collected from China's industrial statistical yearbooks (2007–2015). Emission and abatement data on SO_2, NO_x and Soot are collected from China's environmental statistical yearbooks (2007–2015). Since the statistical authority of China does not report CO_2 emissions of thermal power industry, most existing literatures estimate CO_2 emissions based on energy consumption following the IPCC reference approach. We also follow the same practice to calculate energy consumption related CO_2 emissions by using the carbon emission factors for the combustion of coal, oil and natural gas provided in the IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2006) and the conversion factors from physical unit to coal equivalent provided in China's energy statistical yearbooks (NBS, 2009).

Fig. 1 shows the correlation between energy consumption (in million tons of ce) and emissions of CO_2 (in million tons), SO_2 (in thousand tons), NO_x (in thousand tons), and Soot (in thousand tons), which indicate that the estimated CO_2 emission exhibit a relatively higher correction with energy consumption than the observed SO_2, NO_x, and Soot emissions. Fig. 2 illustrates the temporal trends in the levels of inputs and outputs, as well as abatements from 2006 to 2014. During this period, all the inputs, electricity generation and CO_2 emissions shown generally if not continuously increases. The emissions of SO_2 and Soot shown generally decreases and the emission of NO_x significantly increased in the 11th FYP period but started to decrease since 2011. The increases on the abatements of SO_2 and NO_x were obvious, while the increase on abatement of Soot is moderate.

3.2. Environmental efficiency results

Table 2 summarizes the statistics of the distributions of *OE* and its components of *TE* and *NAE*. Note that the results on *PAE* are omitted here since we only have one polluting input (total energy consumption) in the estimation and there is no polluting input reallocation, thus all values on *PAE* are unit one which will not be further discussed in this study.[5] The mean *TE* values of 0.799, 0.869, 0.988 and 0.956 for SO_2, NO_x, Soot and CO_2 suggest that, on average, China's regional thermal power industry sectors should be able to produce their current output (electricity) given the same inputs (energy, capacity and employee) with 20.1%, 13.1%, 0.2% and 4.4% fewer emissions of SO_2, NO_x, Soot and CO_2, respectively, if they are operating at the production frontier with benchmark technology. The mean *PAE* values of 0.911, 0.918 and 0.993 of SO_2, NO_x and Soot suggest that, on average, China's regional thermal power industry sectors should be able to generate their current electricity with 8.9%, 8.2% and 0.7% fewer emissions of SO_2, NO_x and Soot, respectively, if they appropriately adjust their inputs of energy, capacity and employee and reach an optimal mix of polluting and non-polluting inputs. In addition, the mean *PAE* value of 0.959 of CO_2 suggest that, the average thermal power industry sector of China should be able to generate their current electricity with 4.1% fewer emissions of CO_2 through replacing its current energy input with high quality energy input (e.g., high calorific value coal that contains relative less carbon mass), as well as adjusting both its polluting and non-polluting inputs to reach an optimal input mix. According to the values on both *OE* and its components of *TE* and *NAE*, it can be seen that approximately 60–70% of overall inefficiency is due to technical inefficiency (i.e., thermal power industry is operating below the production frontier) and 30–40% is due to input allocative inefficiency (i.e., thermal power industry is utilizing a sub-optimal mix of inputs) for SO_2, NO_x and Soot, while such contributions of technical inefficiency and input allocative inefficiency to overall inefficiency for CO_2 is approximate 50% to 50%.

Fig. 3 shows the average environmental efficiency (*OE*, *TE* and *NAE*) differences between the 11th and the 12th FYP periods, and Fig. 4 further shows the differences on *OE* for all observations, in which the vertical-axis indicates *OE*, and the horizontal-axis indicates the amount of pollutant emissions. The area of the bubble indicates the amount of electricity generation. It can be seen in Fig. 4 that: (i) For most of regional thermal power industry sectors, their amounts of SO_2 emission obviously decreased while the associated specific SO_2 environmental efficiency increased from the 11th FYP period to the 12th FYP period, which can be observed from the a northwest concentrating trend for the bubbles shown in the upper-left sub-figure. (ii) However, such trend could not be observed for NO_x or Soot since the distributions of their bubbles appear homogeneous in these two periods. (iii) A northeast moving trend for the bubbles shown in the lower-right sub-figure indicates the increase in the amount of CO_2 emission associated with the promotion in the level of specific CO_2 environmental efficiency happens on most of regional thermal power industry sectors. The K-W statistical tests confirm the increases on *OE* for SO_2, NO_x and CO_2; the increases on *TE* for SO_2, NO_x and CO_2; and the increases on *NAE* for CO_2 in China's regional thermal power industry from the 11th FYP period to the 12th FYP period, which also can be observed in Fig. 3. While the environmental efficiency (*OE*, *TE* and *NAE*) changes for Soot, and the *NAE* changes for SO_2 and NO_x are insignificant between these two periods.

[5] Further studies that divide the input of total energy consumption into the consumptions of coal, oil and natural gas (e.g., Wang and Wei, 2016) will lead to the estimation of polluting input allocative environmental efficiency achievable, and based on those results, specific policy implications on how to adjust energy consumption structure for thermal power generation can be derived.

Table 2
Environmental efficiency measures.

Efficiency measures		Technical efficiency (*TE*)			Input allocative efficiency (*NAE*)			Overall efficiency (*OE*)		
		11th FYP	12th FYP	Entire period	11th FYP	12th FYP	Entire period	11th FYP	12th FYP	Entire period
SO_2	Mean	0.724	0.892	0.799	0.904	0.919	0.911	0.651	0.816	0.724
	St. Dev.	0.285	0.192	0.261	0.156	0.134	0.147	0.287	0.209	0.268
	Min	0.198	0.327	0.198	0.267	0.459	0.267	0.194	0.308	0.194
	Max	1	1	1	1	1	1	1	1	1
NO_x	Mean	0.832	0.914	0.869	0.92	0.916	0.918	0.767	0.834	0.797
	St. Dev.	0.185	0.155	0.177	0.116	0.137	0.125	0.206	0.183	0.198
	Min	0.429	0.449	0.429	0.538	0.501	0.501	0.408	0.439	0.408
	Max	1	1	1	1	1	1	1	1	1
Soot	Mean	0.986	0.991	0.988	0.995	0.991	0.993	0.981	0.982	0.981
	St. Dev.	0.024	0.019	0.022	0.009	0.02	0.015	0.026	0.027	0.026
	Min	0.86	0.91	0.86	0.959	0.895	0.895	0.86	0.875	0.86
	Max	1	1	1	1	1	1	1	1	1
CO_2	Mean	0.938	0.977	0.956	0.942	0.98	0.959	0.884	0.958	0.917
	St. Dev.	0.089	0.05	0.077	0.085	0.041	0.071	0.121	0.064	0.106
	Min	0.543	0.759	0.543	0.642	0.753	0.642	0.527	0.662	0.527
	Max	1	1	1	1	1	1	1	1	1

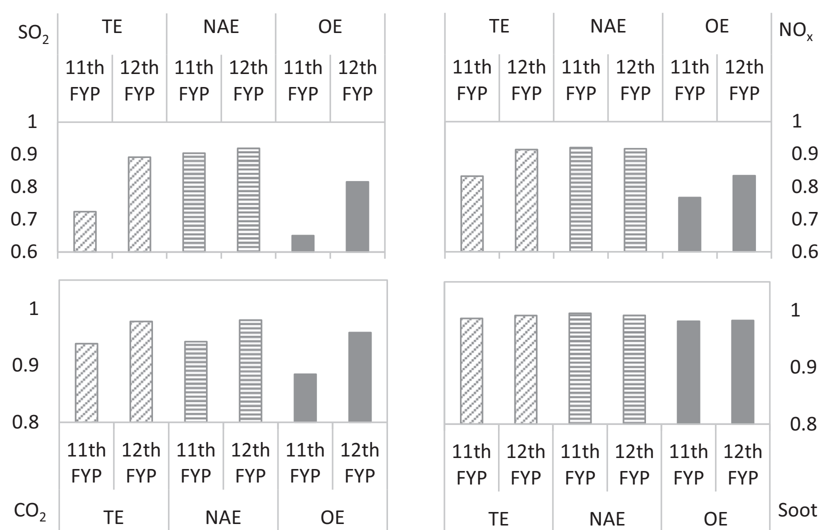

Fig. 3. Average environmental efficiency differences between 11th and 12th FYP periods.

The above results indicate that the regulations for SO_2 and NO_x emissions control implemented in China's thermal power industry during the 11th and 12th FYP periods might help increasing their overall environmental efficiencies, and the significant increases on technical efficiencies of SO_2 and NO_x are the major contributions. Although there was no direct regulation for CO_2 emission reduction during these periods, the indirect regulation on energy consumption intensity reduction for coal-fired power generation implemented in China's thermal power industry might lead a similar result on CO_2 efficiency promotion. In addition, such promotion is contributed by both the technical efficiency increase (i.e., approaching the electricity production frontier by utilizing benchmark technology and promoting the coal quality so as to reduce the carbon mass bound in polluting input) and the input allocative efficiency increase (i.e., optimizing the polluting and non-polluting input mix).

The above environmental efficiency evaluation results could provide us with more implications if we extrapolate them to the estimations of pollutant emission reduction potentials achievable from technical efficiency promotion and input allocation efficiency promotion. Therefore, in the next, we will compare the current practices of electricity generations in China's thermal power industry with the best practices that could be achieved if each regional thermal power industry sector adopts best practice. Fig. 5 shows the accumulated plots of pollutant emission reduction potentials and their minimized emissions for SO_2, NO_x, Soot and CO_2, respectively. In Fig. 5, the vertical-axis indicates the amount of emission and emission reduction potential, the horizontal-axis denotes the observations ranked in emission ascending order (small chart with three categories of bars) or emission reduction potential ascending order (large chart with two categories of bars). On the horizontal-axis of each large chart, the observations could also be seen as ranked in the order of the most to the least environmental efficient thermal power industry sector. The black bar indicates the minimized emission if the thermal power industry sector adopts best practice; the light gray bar indicates the emission reduction potential if the technical inefficiency is eliminated; the dark gray bar indicates the emission reduction potential if the input allocative inefficiency is additional eliminated. Note that, since the MBP is applied for estimating pollutant environmental efficiency, the light gray bar for pollutant emission indicates the emission reduction potential achievable from both technical efficiency promotion and energy input quality promotion.

From Fig. 5, first it can be seen from four small charts that the relative emission reduction potentials for SO_2 and NO_x are much higher, followed by that for CO_2. While the reduction potential for Soot emission is relatively lowest. This result suggests that tighter regulations on SO_2 and NO_x control should be continuously

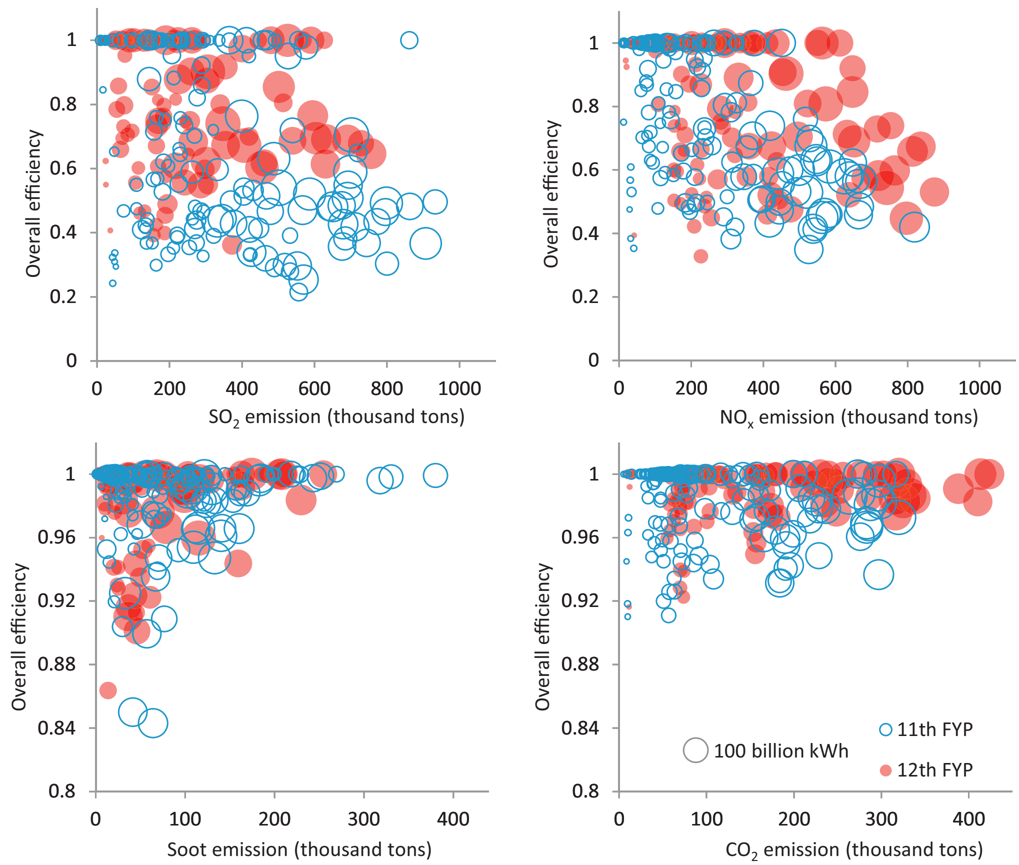

Fig. 4. Differences on overall environmental efficiencies, emissions and electricity generations between 11th and 12th FYP periods.

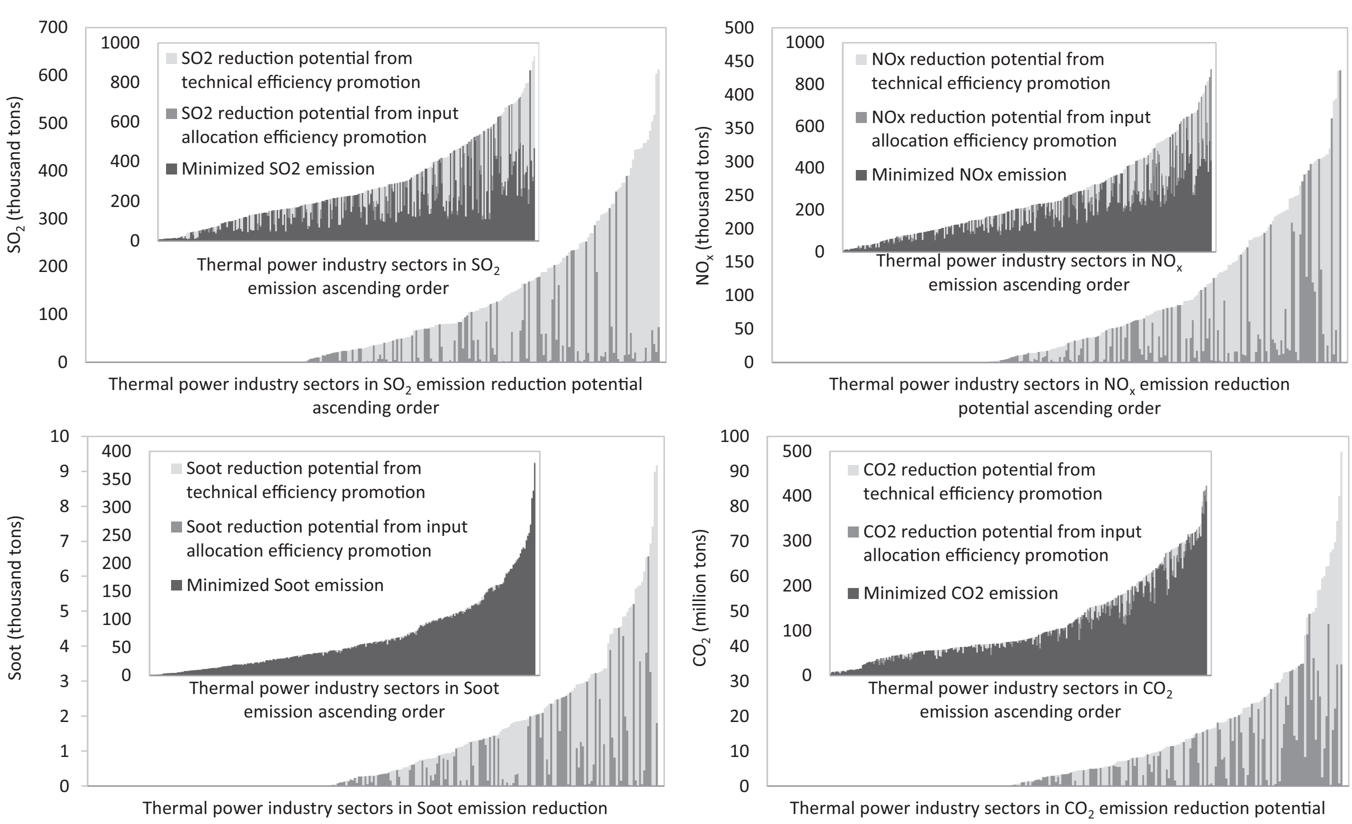

Fig. 5. Emission reduction potentials.

Table 3
Abatement efficiency measures.

Efficiency measures		Technical abatement efficiency			Input allocative abatement efficiency		
		11th FYP	12th FYP	Entire period	11th FYP	12th FYP	Entire period
SO_2	Mean	0.829	0.987	0.899	0.818	0.990	0.895
	St. Dev.	0.256	0.040	0.208	0.272	0.033	0.221
	Min	0.011	0.740	0.011	0.012	0.787	0.012
	Max	1	1	1	1	1	1
NO_x	Mean	0.586	0.823	0.691	0.534	0.688	0.602
	St. Dev.	0.419	0.321	0.396	0.415	0.366	0.401
	Min	0.003	0.004	0.003	0.002	0.004	0.002
	Max	1	1	1	1	1	1
Soot	Mean	0.954	0.976	0.964	0.954	0.962	0.957
	St. Dev.	0.120	0.071	0.102	0.119	0.086	0.106
	Min	0.309	0.585	0.309	0.331	0.584	0.331
	Max	1	1	1	1	1	1

implemented in China's thermal power industry to stimulate technical promotion and to optimize input resources allocation, since up to the end of the 12th FYP period there still exist larger potentials in SO_2 and NO_x emission reductions in this industry sector. However, the relatively low potential on Soot emission reduction suggests that moderate regulation on Soot control should be implemented, since additional reduction on Soot may lead to accelerated increase in electricity consumption for operating the scrubbers, or one has to find extra and new technologies for Soot reduction which might be more expensive. Similar moderate regulation on CO_2 emission control is suggested, since the end-of-pipe abatement technology, e.g., Carbon Capture and Storage (CCS), is not common and not economically feasible if not totally technically impossible in China's thermal power industry at the current stage.

From Fig. 5, it is obvious from the large charts that the light gray bars dominant the dark gray bars (i.e., the occurrence of light gray bars are more frequent than that of dark gray bars) for SO_2, NO_x and Soot, indicating that more emission reduction potentials come from technical efficiency promotion than input resources reallocation for SO_2, NO_x and Soot. While there is no obvious difference between the occurrences of the light gray bars and the dark gray bars for CO_2. These results again confirm that technical efficiency promotion associated with energy quality promotion should play a more critical role than adjusting input mix on the environmental efficiency promotion and the reduction of SO_2, NO_x and Soot emissions in China's thermal power industry during the 11th and 12th FYP periods, while technical efficiency increase combined with energy quality promotion, and input resources reallocation should contribute equally in leading the environmental efficiency promotion and the reduction of CO_2 emission in this industry during the same periods. This difference on environmental inefficiency patterns and emission reduction potential patterns between CO_2 emission and other three pollutant emissions also confirms that the introducing of MBP could provide a more appropriate and accurate environmental efficiency evaluation for the case of China's thermal power industry where the end-of-pipe abatements are gradually implemented for SO_2, NO_x and Soot emissions but is not common for CO_2 emission.

To further extend the implications of the environmental efficiency results, we undertake a calculation of the environmental gains for the thermal power industry sector from adopting best practice. The estimations show that, for the entire thermal power industry, an annual average amount to 2.92 million tons of SO_2 could be reduced during the 11th and 12th FYP periods which accounts for 34.4% of the actual annual SO_2 emission. Accordingly, for NO_x and Soot, the annual average amounts on emission reductions are 2.13 and 0.35 million tons, which account for 26.8% and 1.69% of their actual annual emissions, respectively. In addition, if the technical inefficiency and input allocative inefficiency are ideally eliminated, the annual average CO_2 emission of the entire thermal power industry could reduce by 3.17 million tons accounting for 8.97% of the actual annual CO_2 emission. Note that although these estimated potentials for pollutant emission reductions in China's thermal power industry are substantial amounts, the realizations of which are costly, since in specific regional thermal power industry sectors, possible extra and more expensive technologies may needed for technical efficiency promotion, and the adjustment of input mix may result in increased cost in the case that the relative prices of equipment and labor inputs are higher than that of energy input.

3.3. Abatement efficiency results

Different from most of the existing studies with MBP in environmental efficiency measurement, in this study, we additionally emphasize the measurement of pollution abatement activities in the efficiency evaluation. This section reports the abatement efficiency results. Table 3 provides the statistics of the distribution of *ATE* and *ANAE*. For the same reason that there is no polluting input reallocation in our estimation, as pointed out in Section 3.2, we do not discuss the results of *APAE*.

From Table 3 we can find that, the mean technical abatement efficiency (*ATE*) scores for SO_2, NO_x and Soot are 0.899, 0.691, and 0.964, respectively, for the entire study period. These results suggest that the average thermal power industry sector of China should be able to increase their abatements of SO_2, NO_x and Soot by 10.1%, 30.9% and 3.7%, respectively, with their current electricity generation and input resources unchanged, if it is operating on the abatement technology frontier. Furthermore, the mean input allocative abatement efficiency (*ANAE*) scores for SO_2, NO_x and Soot of 0.895, 0.602 and 0.957 suggest that the average thermal power industry sector of China should be able to increase their abatements of SO_2, NO_x and Soot by 10.5%, 39.8% and 4.3%, respectively, with their current electricity generation unchanged, if it is adopting the best practice, i.e., operating on the abatement technology frontier associated with using an optimal mix of input resources.

Fig. 6 shows the average abatement efficiency difference between the 11th and 12th FYP periods. The K-W statistical tests confirm the increases on both *ATE* and *ANAE* for SO_2 and NO_x in China's regional thermal power industry from the 11th FYP period to the 12th FYP period, while the abatement efficiency changes for Soot are insignificant between these two periods. These results provide another possible support for the effectiveness of the regulations for SO_2 and NO_x emissions control on promoting the environmental performance of China's thermal power industry. In another words, the regulations on SO_2 and NO_x emissions control might stimulate the application and promotion of the end-of-pipe abatement technologies for SO_2 and NO_x, and help to optimize the utilization of input mix in this industry sector.

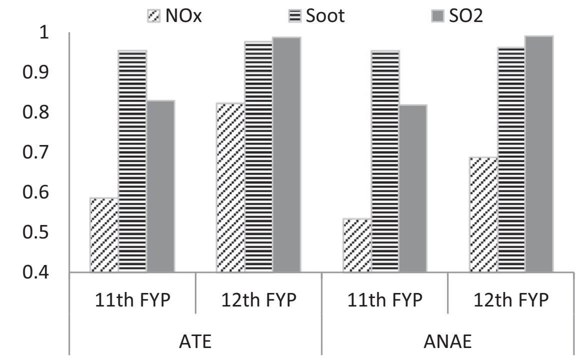

Fig. 6. Average abatement efficiency differences between 11th and 12th FYP periods.

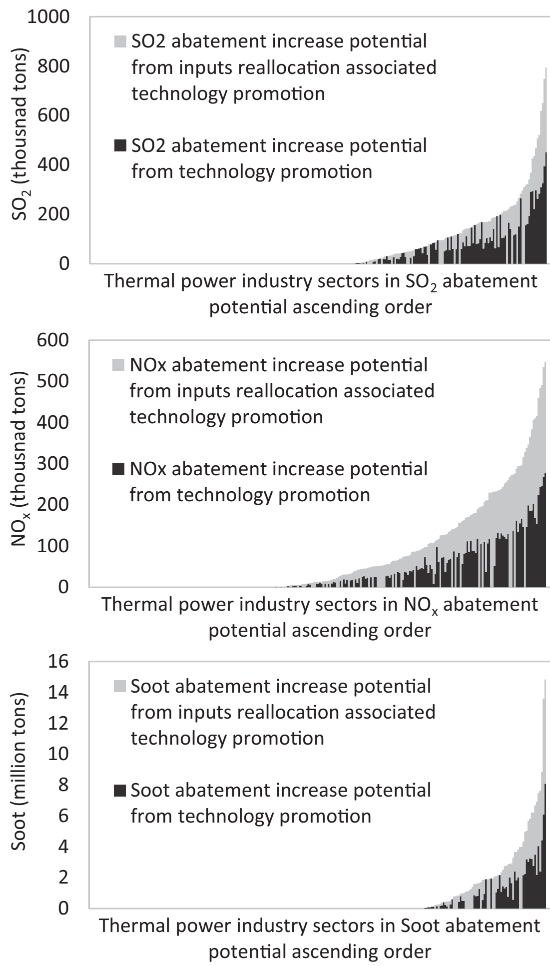

Fig. 7. Abatement increase potentials.

Fig. 7 additionally provides accumulated plots of pollutant abatement increase potentials for SO_2, NO_x and Soot, respectively, which show the maximized abatements achievable for each regional thermal power industry sector if it adopts best practice. The vertical-axis of each chart in Fig. 7 indicates the amount of abatement increase potential, and the horizontal-axis denotes the observations ranked in the order of the most to the least abatement efficient thermal power industry sector. The dark gray bars indicate the abatement increase potentials from pure technology promotion, and the light gray bars indicate the potentials from inputs reallocation associated technology promotion.

It is clear in Fig. 7 that, the frequencies of occurrence of light gray bars are similar with those of dark gray bars for all three pollutants, indicating that both the pure technical abatement efficiency promotion and the input allocative abatement efficiency promotion play similar roles in eliminating the abatement increase potentials for SO_2, NO_x and Soot. This result suggests that to further promote abatement efficiency in China's thermal power industry, regulations on stimulating the development and popularization of end-of-pipe abatement technologies should take priority at the current stage instead of additionally suggesting input mix adjustment, since the latter may result in additionally increased abatement costs.

Before ending this section, we similarly calculate and report the abatement gains for China's thermal power industry sector from adopting best abatement practice. The calculations show that, for the entire thermal power industry, the annual average increases on the abatements of SO_2, NO_x and Soot of 1.92 million tons, 2.21 million tons and 21.39 million tons, respectively, would be realized during the 11th and 12th FYP periods if all the pollutant abatement inefficiencies are ideally eliminated. However, we must recognize that according to the calculation shown in Fig. 7, approximate one half of these abatement potentials would be realized through end-of-pipe abatements, while the utilizing of end-of-pipe abatement technologies, e.g., SO_2 and NO_x scrubbers, for reducing their emissions will inevitably affect the emission of CO_2 and generation of electricity. For example, the operation of scrubbers in a power plan will result in increased consumptions of electricity, and accordingly increased energy input and associated CO_2 emission for generating electricity. Furthermore, the chemical processes (e.g., $SO_2 + CaCO_3 = CaSO_3 + CO_2$) for absorbing sulphur and nitrogen will also result in additional CO_2 emission.

3.4. Efficiency change results

So far we have analysed the environmental and abatement efficiency levels, as well as optimized pollutant emissions and abatements could be achieved by adopting best practices through technical efficiency promotion and input allocative efficiency promotion. Next, we provide the measurements of environmental efficiency changes and the decompositions of these changes for China's thermal power industry, so as to identify the trends on the efficiency changes and the driving forces of these changes. Fig. 8 illustrates the patterns of movements of *OEC* and its components (*TEC* and *NAEC*) of four pollutant emissions for the whole thermal power industry of China from 2006-2014 which are all presented in their annually accumulated index forms.

In Fig. 8 we can see that the specific overall environmental efficiencies of SO_2, NO_x and CO_2 experienced continuously growths in almost all years of the study period (with only one year's exception of negative growth occurred in 2007 for NO_x and CO_2), in which the growth of SO_2 environmental efficiency is most significant. However, the pattern of change on overall environmental efficiency of Soot presents a different picture, where negative growth occurred in four years (2007–2008 and 2010–2011) and the efficiency change during the entire study period is not obvious. Fig. 8 also indicates that technical efficiency changes and input allocative efficiency changes contribute approximately equally to the overall environmental efficiency changes of NO_x, CO_2 and Soot; while the obvious increase in technical efficiency is the major driving force for overall environmental efficiency promotion of SO_2. Fig. 9 compares the specific environmental efficiency changes of four pollutant emissions. For the entire China's thermal power industry and over the 11th and 12th FYP periods, the growth on SO_2 overall environmental efficiency is most significant follow by the growth on NO_x overall environmental efficiency, while the overall environmental efficiency of Soot barely changed. The

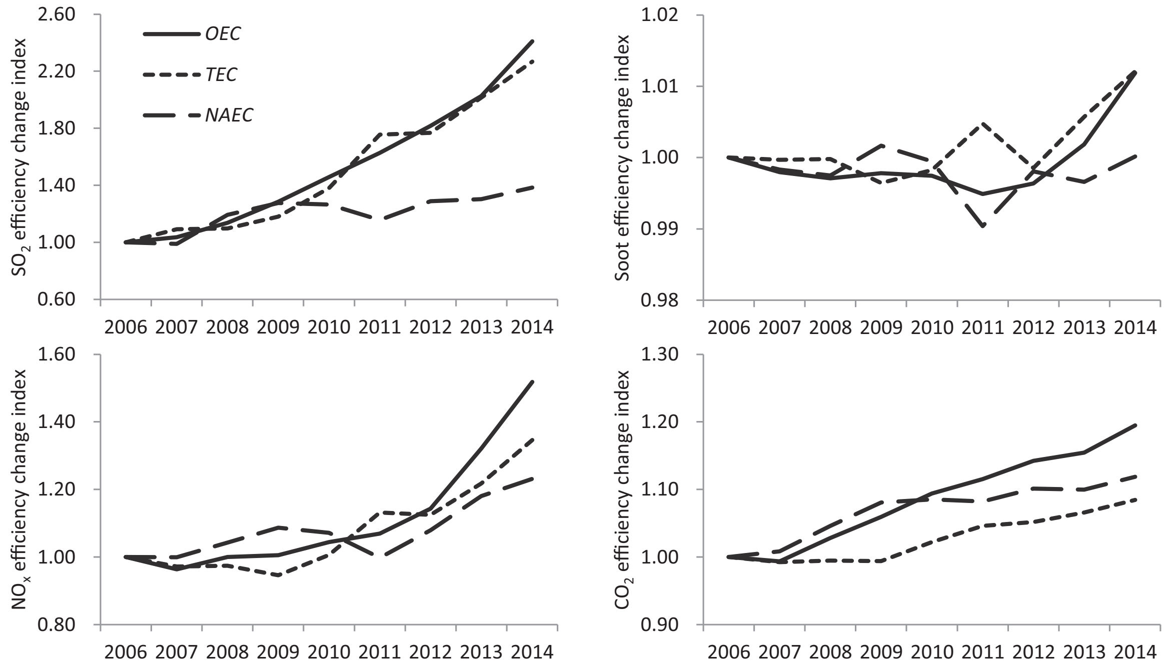

Fig. 8. Accumulated overall environmental efficiency change indices and their decompositions.

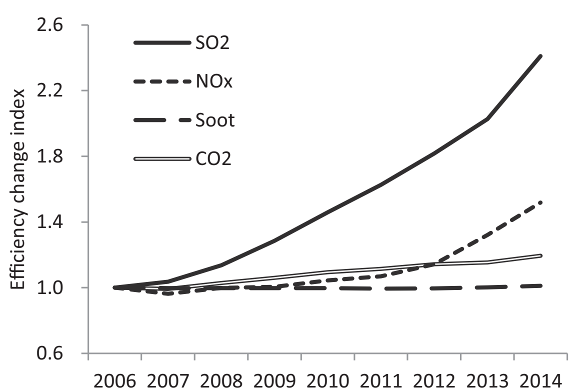

Fig. 9. Accumulated overall environmental efficiency change indices.

growth on CO_2 overall environmental efficiency is faster than that of NO_x before 2011, while the latter exceeds the former since 2012.

3.5. Efficiency differences between modelling with and without MBP

In order to verify the necessity of introducing the MBP in environmental production technology so as to appropriately account for the laws of thermodynamics in environmental efficiency evaluation and the identification of emission reduction potential, we also estimate the environmental efficiency (*OE*, *TE* and *NAE*) and the abatement efficiency (*ANAE*) for four pollutants using the traditional environmental production technology based estimation without the assumption of MBP, i.e., weak disposability assumption based environmental and abatement efficiency evaluation. The evaluation results are compared with the results from the MBP models, which are reported in Table 4 and shown in Figs. 10 and 11.

From Table 4, it can be observed that the average overall environmental efficiency from the no MBP models are 0.459, 0.627, 0.528 and 0.814 for SO_2, NO_x, Soot and CO_2, respectively, which are all below their counterparts from the MBP models (where the values are 0.724, 0.797, 0.981 and 0.917, respectively). However, the average non-polluting & polluting input allocative abatement efficiency from the no MBP models are 0.899, 0.691 and 0.976 for SO_2, NO_x and Soot, respectively, which are all above their counterparts from the MBP models (where the values are 0.807, 0.440 and 0.964). Fig. 10 provides the same results that the no MBP models tend to underestimate the environmental efficiency compared with the MBP models, since most of bubbles indicating the CO_2 environmental efficiency levels in Fig. 10 are located below the diagonal lines. The K-W statistical tests additionally confirm that the CO_2 environmental efficiencies derived from the no MBP models are significant lower than those from the MBP models. Because the end-of-pipe abatements of SO_2, NO_x and Soot can have synergy effects on CO_2 emission, we also implement such comparisons for SO_2, NO_x and Soot, where similar differences can be observed in Fig. 10 and statistically confirmed for almost all values on *OE*, *TE*, and *NAE* of SO_2, NO_x and Soot, with just two exceptions for the *NAE* values of SO_2 and NO_x.

Fig. 11 shows the comparisons of *ANAE* with and without MBP. It can be seen that, on the contrary, the no MBP models tent to overestimate the abatement efficiency compared with the MBP models, since most of bubbles indicating the abatement efficiency levels of SO_2, NO_x and Soot in Fig. 11 are located above the diagonal lines. The K-W statistical tests also confirm that the abatement efficiencies derived from the no MBP models are significant higher than those from the MBP models for all three pollutants.

Table 4
Environmental and abatement efficiency measures with and without MBP.

Efficiency measures		Mean *TE*	Mean *NAE*	Mean *OE*	Mean *ANAE*
SO_2	Without MBP	0.510	0.914	0.459	0.899
	With MBP	0.799	0.911	0.724	0.807
NO_x	Without MBP	0.688	0.925	0.627	0.691
	With MBP	0.869	0.918	0.797	0.440
Soot	Without MBP	0.572	0.938	0.528	0.976
	With MBP	0.988	0.993	0.981	0.964
CO_2	Without MBP	0.869	0.934	0.814	–
	With MBP	0.956	0.959	0.917	–

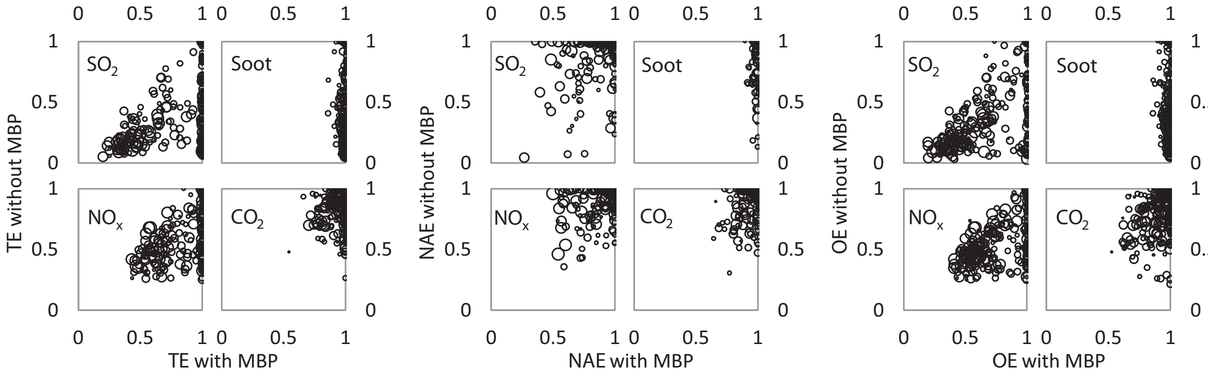

Fig. 10. Comparison of environmental efficiencies with MBP and without MBP.

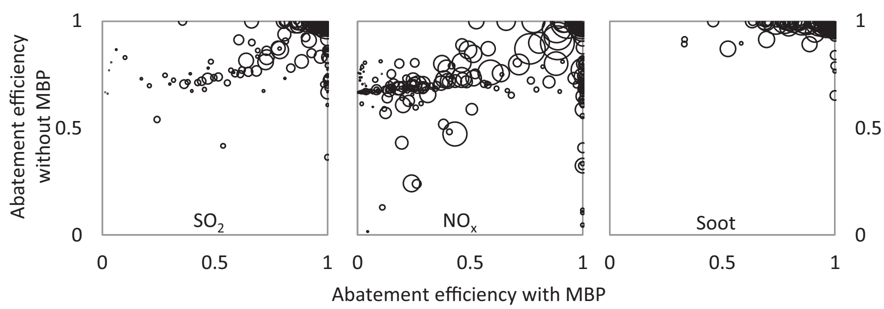

Fig. 11. Comparison of abatement efficiencies with MBP and without MBP.

The identified significant efficiency difference between the above two types of models implies the MBP seems to be more appropriate for modelling the environmental efficiency where the end-of-pipe abatement is not common (especially for CO_2 emission). On the one hand, the MBP guarantees the satisfaction of the laws of thermodynamics, and on the other hand, the MBP model does provide a different but more accurate estimation of efficiency since the MBP models put more emphasis on reducing emissions and improve abatements through refining the polluting input (i.e., increasing the quality of energy) and optimizing the input mix (i.e., polluting and non-polluting input reallocation), which are not comprehensively, if not totally omitted, included in the no MBP models.

4. Conclusion

In this study we proposed a DEA based generalized approach that is combined with the materials balance principle to jointly evaluate environmental and abatement efficiency. The proposed approach is along the line of weak G-disposability assumption based modelling but is an extension to existing models that in our approach the identification of all possible adjustments on polluting mass bound in inputs and outputs, as well as potential adjustments on abatement of pollutants are emphasized. The overall environmental efficiency estimated by the approach is further decomposed into the measures of technical efficiency, polluting inputs allocative efficiency, and all inputs (i.e., polluting and non-polluting inputs) allocative efficiency with the highlight of incorporating pollution abatement activities in the efficiency measure. Thus, several new measures of abatement efficiency are additionally proposed in this study which help to identify the pollutant abatement potentials achievable from end-of-pipe abatement technology promotion associated with polluting input quality promotion and input resources reallocation. At last, several global Malmquist productivity indices for identifying the changes on environmental and abatement efficiency are proposed. This approach is applied to China's thermal power industry and several empirical results are derived.

During our study period (2006–2014), the regulations for SO_2, NO_x and Soot emissions reduction were implemented in China's thermal power industry, while there is no direct regulation for CO_2 emission reduction in this industry. In addition, although the end-of-pipe abatement activities for SO_2, NO_x and Soot were gradually implemented for thermal power generation during this period, CO_2 emission from power plants in China are currently not directly constrained since the end-of-pipe technologies for CO_2 emission control are currently not commercialized, and furthermore, the pilot projects of Carbon Capture and Storage are not common in China's thermal power industry at the current stage. Consider the different abatement activities between carbon and other major air pollutants, the environmental efficiency patterns of CO_2 and other three pollutants should present different pictures. According to the results of overall environmental efficiency and its component of technical efficiency and input allocative efficiency, it is clear that approximate two thirds of overall inefficiencies of SO_2, NO_x and Soot are due to technical inefficiency, i.e., the thermal power industry is operating below the electricity production frontier, and approximate one third of overall inefficiencies are due to input allocative inefficiency, i.e., thermal power industry is utilizing a sub-optimal mix of energy (polluting) input and other non-energy (non-polluting) inputs. However, the pattern on the contributions of technical inefficiency and input allocative inefficiency to overall inefficiency for CO_2 is quite different which is approximate fifty to fifty percent.

The identified environmental efficiency differences between the 11th to 12th FYP periods in this study provide evidences that the direct regulations for SO_2 and NO_x emissions control in China's thermal power industry may have helped increasing their overall environmental efficiencies which are mainly due to the significant improvements on technical efficiencies of SO_2 and NO_x. Besides, the indirect regulation on CO_2 emission control (i.e., regulation for reducing net coal consumption rate of electricity generation) might

also lead CO_2 overall environmental efficiency promotion which is approximately equally contributed by technical efficiency improvement and input allocative efficiency improvement. In addition, since the materials balance principle is implemented for modelling all pollutants in this study, it should be noticed that the identified overall environmental efficiency increases of them in China's thermal power industry are derived from both the technical efficiency increases associated with the promotion on coal quality (resulting in the reduction of polluting mass bound in the coal), and the optimization of polluting and non-polluting input mix.

We extrapolate the environmental efficiency evaluation to the environmental gains estimation (i.e., emissions reduction potentials achievable from technical efficiency promotion and input allocation efficiency promotion) in China's thermal power industry. The estimations show annual average amounts to 2.92 million tons of SO_2, 2.13 million tons of NO_x and 3.17 million tons of CO_2 could be reduced, respectively, for the entire thermal power industry from adopting best practice, which account for 34.4%, 26.8% and 8.97% of the actual annual emissions of SO_2, NO_x and CO_2, respectively. This result suggests that tighter regulations on SO_2 and NO_x control are necessary so as to continuously stimulate the development and popularization of abatement techniques and the adjustment of input resource mix, while moderate regulation on CO_2 emission control is appropriate. However, it should be realized that, although there exist substantial potentials on pollutant emission reductions in China's thermal power industry, the realizations of them might costly. In some thermal power industry sectors of specific region, extra and more expensive technologies are needed for eliminating technical inefficiency, and furthermore, to adjust the sub-optimal input mix may result in increased total cost for electricity generation.

In this study, the modelling of pollution abatement activities is emphasized in the efficiency evaluation, and the results on abatement efficiency suggest that to further improve abatement efficiency of SO_2, NO_x and Soot in China's thermal power industry, policies for popularizing the existing high performance end-of-pipe abatement technologies should take priority. Similarly, one should realize that the application of end-of-pipe abatement technologies for reducing SO_2 and NO_x emissions will, at the current stage, inevitably increase the emission of CO_2, because, for example, the chemical processes for absorbing SO_2 and NO_x will result in additional CO_2 emission. Therefore, the pollutant-by-pollutant regulations for emission control may not result in a global optimal abatement performance in the thermal power industry.

At last, the comparison of the efficiency differences between modelling with MBP and without MBP shows that the MBP models provide a different but more accurate picture on the pattern of environmental and abatement efficiency, because the MBP models put more emphasis on reducing emissions and increasing abatements through both adjusting the sub-optimal polluting and non-polluting input mix and improving the quality of polluting input so as to reduce the polluting mass bound in the input.

One limitation in the application of the proposed method in China's thermal power industry is that the results on *PAE* are not available since we did not additionally decompose the total polluting energy input into specific fossil fuel consumptions (e.g., coal, oil and natural gas). Specific estimation of polluting input allocative environmental efficiency is one potential further study that will benefit to the policy making for adjusting energy consumption structure of China's thermal power industry. Furthermore, the application of a network DEA framework, that helps to look inside the black box through explicitly introduce a pollutant abatement activity into the electricity production process, in the efficiency estimation of the thermal power industry is another potential issue for further study. In this case, two sub-technologies, namely the production technology for electricity generation and the abatement technology for emission reduction can be detected and a tradeoff of input resources allocation between production and abatement processes can be optimized and thus, the associated business strategy can be suggested for promoting the performance of thermal power industry from the perspective of both production and environmental protection.

Acknowledgment

We gratefully acknowledge the financial supports from the National Natural Science Foundation of China (grant numbers 71471018, 71521002 and 71642004), the Social Science Foundation of Beijing (grant number 16JDGLB013), the National Key R&D Program (grant number 2016YFA0602603), the Joint Development Program of Beijing Municipal Commission of Education, and the Research Program of State Grid Corporation of China (grant number YD71-16-014). K. Wang would like to thank Prof. F. R. Førsund of University of Oslo for his valuable comments.

References

Adler, N., & Volta, N. (2016). Accounting for externalities and disposability: A directional economic environmental distance function. *European Journal of Operational Research, 250*(1), 314–327.

Ayres, R. U., & Kneese, A. V. (1969). Production, consumption, and externalities. *The American Economic Review, 59*(3), 282–297.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science, 30*(9), 1078–1092.

Bi, G. B., Song, W., Zhou, P., & Liang, L. (2014). Does environmental regulation affect energy efficiency in China's thermal power generation? Empirical evidence from a slacks-based DEA model. *Energy Policy, 66*, 537–546.

Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica, 50*(6), 1393–1414.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444.

Chen, C. M., & Delmas, M. A. (2012). Measuring eco-inefficiency: A new frontier approach. *Operations Research, 60*(5), 1064–1079.

Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management, 51*(3), 229–240.

Chung, Y. H. (1997). *Directional distance functions and undesirable outputs*. Southern Illinois University.

Coelli, T., Lauwers, L., & Van Huylenbroeck, G. (2007). Environmental efficiency measurement and the materials balance condition. *Journal of Productivity Analysis, 28*(1-2), 3–12.

Cooper, W. W., Seiford, L. M., & Zhu, J. (Eds.) (2011). *Handbook on data envelopment analysis* (164). Springer Science & Business Media.

Dakpo, K. H., Jeanneaux, P., & Latruffe, L. (2016). Modelling pollution-generating technologies in performance benchmarking: Recent developments, limits and future prospects in the nonparametric framework. *European Journal of Operational Research, 250*(2), 347–359.

Du, L., He, Y., & Yan, J. (2013). The effects of electricity reforms on productivity and efficiency of China's fossil-fired power plants: An empirical analysis. *Energy Economics, 40*, 804–812.

Duan, N., Guo, J. P., & Xie, B. C. (2016). Is there a difference between the energy and CO_2 emission performance for China's thermal power industry? A bootstrapped directional distance function approach. *Applied Energy, 162*, 1552–1563.

European Environment Agency. (2013). EN08 Emissions (CO2, SO2 and NOx) intensity of public conventional thermal power (electricity and heat) production. Indicator Fact Sheet IND-132-en. http://www.eea.europa.eu/data-and-maps/indicators/en08-emissions-co2-so2-and-1.

Expert Group on Techno-Economic Issues. (2012). Guidance document on control techniques for emissions of sulphur, NOx, VOC, dust (including PM10, PM2.5 and black carbon) from stationary sources. Working Group on Strategies and Review, Fiftieth session. http://www.unece.org/fileadmin/DAM/env/documents/2012/EB/Informal_document_7_EGTEI_guidance-document_on_stationary_sources_tracked_changes_compared_with_WGSR_version.pdf.

Fan, M., Shao, S., & Yang, L. (2015). Combining global Malmquist–Luenberger index and generalized method of moments to investigate industrial total factor CO 2 emission performance: A case of Shanghai (China). *Energy Policy, 79*, 189–201.

Färe, R., & Grosskopf, S. (2004). Modeling undesirable factors in efficiency evaluation: comment. *European Journal of Operational Research, 157*(1), 242–245.

Färe, R., & Grosskopf, S. (1996). *Intertemporal Production Frontiers: With Dynamic DEA*. Kluwer Academic Publishers.

Färe, R., Grosskopf, S., Lindgren, B., & Roos, P. (1992). Productivity changes in Swedish pharamacies 1980–1989: A non-parametric Malmquist approach. *Journal of Productivity Analysis, 3*(1-2), 85–101.

Färe, R., Grosskopf, S., Lovell, C. K., & Pasurka, C. (1989). Multilateral productivity comparisons when some outputs are undesirable: A nonparametric approach. *The Review of Economics and Statistics*, 90–98.

Färe, R., Grosskopf, S., & Pasurka, C. A. (2007a). Environmental production functions and environmental directional distance functions. *Energy, 32*(7), 1055–1066.

Färe, R., Grosskopf, S., & Pasurka, C. A. (2007b). Pollution abatement activities and traditional productivity. *Ecological Economics, 62*(3), 673–682.

Färe, R., Grosskopf, S., & Pasurka, C. (2013). Joint production of good and bad outputs with a network application. *Encyclopedia of Energy, Natural Resources and Environmental Economics, 2*, 109–118.

Førsund, F. R. (2009). Good modelling of bad outputs: Pollution and multiple-output production. *International Review of Environmental and Resource Economics, 3*(1), 1–38.

Hailu, A., & Veeman, T. S. (2001). Non-parametric productivity analysis with undesirable outputs: An application to the Canadian pulp and paper industry. *American Journal of Agricultural Economics, 83*(3), 605–616.

Hampf, B. (2014). Separating environmental efficiency into production and abatement efficiency: A nonparametric model with application to US power plants. *Journal of Productivity Analysis, 41*(3), 457–473.

Hampf, B., & Rødseth, K. L. (2015). Carbon dioxide emission standards for US power plants: An efficiency analysis perspective. *Energy Economics, 50*, 140–153.

Hoang, V. N., & Rao, D. P. (2010). Measuring and decomposing sustainable efficiency in agricultural production: A cumulative exergy balance approach. *Ecological economics, 69*(9), 1765–1776.

Hoang, V. N., & Coelli, T. (2011). Measurement of agricultural total factor productivity growth incorporating environmental factors: A nutrients balance approach. *Journal of Environmental Economics and Management, 62*(3), 462–474.

IPCC. (2006). *IPCC guidelines for national greenhouse gas inventories: Volume II energy*. Japan: Institute for Global Environmental Strategies.

Leleu, H. (2013). Shadow pricing of undesirable outputs in nonparametric analysis. *European Journal of Operational Research, 231*(2), 474–480.

Murty, S., Russell, R. R., & Levkoff, S. B. (2012). On modeling pollution-generating technologies. *Journal of Environmental Economics and Management, 64*(1), 117–135.

NBS. (2009). *China energy statistical yearbook*. Beijing, China: National Bureau of Statistics of People's Republic of China (NBS).

Oh, D. H. (2010). A global Malmquist-Luenberger productivity index. *Journal of productivity analysis, 34*(3), 183–197.

Pastor, J. T., & Lovell, C. K. (2005). A global Malmquist productivity index. *Economics Letters, 88*(2), 266–271.

Rødseth, K. L. (2016). Environmental efficiency measurement and the materials balance condition reconsidered. *European Journal of Operational Research, 250*(1), 342–346.

Sahoo, B. K., Luptacik, M., & Mahlberg, B. (2011). Alternative measures of environmental technology structure in DEA: An application. *European Journal of Operational Research, 215*(3), 750–762.

SCC. (2007). State Council of the People's Republic of China: Comprehensive Work Plan for Energy Conservation and Emissions Reduction.

SCC. (2011). State Council of the People's Republic of China: Plan for Energy Conservation and Emissions Reduction in the 12th Five Year Plan Period.

Scheel, H. (2001). Undesirable outputs in efficiency valuations. *European Journal of Operational Research, 132*(2), 400–410.

Seiford, L. M., & Zhu, J. (2002). Modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research, 142*(1), 16–20.

Seiford, L. M., & Zhu, J. (2005). A response to comments on modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research, 161*(2), 579–581.

SERC. (2011). State electricity regulatory commission of the People's Republic of China: Energy and emission reduction conditions of the power industry in 2010 and during the 11th Five Year Plan period.

Sueyoshi, T., & Goto, M. (2012). Data envelopment analysis for environmental assessment: Comparison between public and private ownership in petroleum industry. *European Journal of Operational Research, 216*(3), 668–678.

Wang, K., Lee, C. Y., Zhang, J., & Wei, Y. M. (2016). Operational performance management of the power industry: A distinguishing analysis between effectiveness and efficiency. *Annals of Operations Research* in press. doi:10.1007/s10479-016-2189-1.

Wang, K., & Wei, Y. M. (2016). Sources of energy productivity change in China during 1997–2012: A decomposition analysis based on the Luenberger productivity indicator. *Energy Economics, 54*, 50–59.

Wang, K., Wei, Y. M., & Zhang, X. (2012). A comparative analysis of China's regional energy and emission performance: Which is the better way to deal with undesirable outputs? *Energy Policy, 46*, 574–584.

Wang, K., Wei, Y. M., & Zhang, X. (2013). Energy and emissions efficiency patterns of Chinese regions: A multi-directional efficiency analysis. *Applied Energy, 104*, 105–116.

Wang, K., Xian, Y., Wei, Y. M., & Huang, Z. (2016). Sources of carbon productivity change: A decomposition and disaggregation analysis based on global Luenberger productivity indicator and endogenous directional distance function. *Ecological Indicators, 66*, 545–555.

Wang, K., Zhang, X., Yu, X., Wei, Y. M., & Wang, B. (2016). Emissions trading and abatement cost savings: An estimation of China's thermal power industry. *Renewable and Sustainable Energy Reviews, 65*, 1005–1017.

Welch, E., & Barnum, D. (2009). Joint environmental and cost efficiency analysis of electricity generation. *Ecological Economics, 68*(8), 2336–2343.

Yang, H., & Pollitt, M. (2009). Incorporating both undesirable outputs and uncontrollable variables into DEA: The performance of Chinese coal-fired power plants. *European Journal of Operational Research, 197*(3), 1095–1105.

Zhao, X., Yin, H., & Zhao, Y. (2015). Impact of environmental regulations on the efficiency and CO_2 emissions of power plants in China. *Applied Energy, 149*, 238–247.

Zhou, P., Ang, B. W., & Poh, K. L. (2006). Slacks-based efficiency measures for modeling environmental performance. *Ecological Economics, 60*(1), 111–118.

Zhu, J. (2014). *Quantitative models for performance evaluation and benchmarking: Data envelopment analysis with spreadsheets*: 213. Springer.